Investigating Tafheet as a Unique Driving Style Behaviour

PhD Thesis

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Dedication

To my father

Mohammed Aldawsari

For his inspiration and motivation. Without his endless support, I could not have

Completed my studies.

To my mother

Albandary Alhammed

For her prayers, endless love, support, and belief in me.

To my wife

Maha Aldawsari

For being on my side during the critical times and for her unflinching love.

To my son

Mohammed

For his patience and prayers for my success.

Abstract:

Road safety has become a major concern due to the increased rate of deaths caused by road accidents. For this purpose, intelligent transportation systems are being developed to reduce the number of fatalities on the road. A plethora of work has been undertaken on the detection of different styles of behaviour such as fatigue and drunken behaviour of the drivers; however, owing to complexity of human behaviour, a lot has yet to be explored in this field to assess different styles of the abnormal behaviour to make roads safer for travelling. This research focuses on detection of a very complex driver's behaviours: 'tafheet', reckless and aggressive by proposing and building a driver's behaviour detection model in the context-aware system in the VANET environment. Tafheet behaviour is very complex behaviour shown by young drivers in the Middle East, Japan and the USA. It is characterised by driving at dangerously high speeds (beyond those commonly known in aggressive behaviour) coupled with the drifting and angular movements of the wheels of the vehicle, which is similarly aggressive and reckless driving behaviour. Thus, the dynamic Bayesian Network (DBN) framework was applied to perform reasoning relating to the uncertainty associated with driver's behaviour and to deduce the possible combinations of the driver's behaviour based on the information gathered by the system about the foregoing factors.

Based on the concept of context-awareness, a novel Tafheet driver's behaviour detection architecture had been built in this thesis, which had been separated into three phases: sensing phase, processing and thinking phase and the acting phase. The proposed system elaborated the interactions of various components of the architecture with each other in order to detect the required outcomes from it. The implementation of this

proposed system was executed using GeNIe 2.0 software, resulting in the construction of DBN model. The DBN model was evaluated by using experimental set of data in order to substantiate its functionality and accuracy in terms of detection of tafheet, reckless and aggressive behaviours in the real time manner. It was shown that the proposed system was able to detect the selected abnormal behaviours of the driver based on the contextual data collected. The novelty of this system was that it could detect the reckless, aggressive and tafheet behaviour in sequential manner, based on the intensity of the driver's behaviour itself. In contrast to previous detection model, this research work suggested the On Board Unit architecture for the arrangement of sensors and data processing and decision making of the proposed system, which can be used to pre-infer the complex behaviour like tafheet. Thus it has the potential to prevent the road accidents from happening due to tafheet behaviour.

Declaration

I declare that the work described in this thesis is original work undertaken by me for the degree of Doctor of Philosophy, at the software Technology Research Laboratory (STRL), at De Montfort University, United Kingdom.

No part of the material described in this thesis has been submitted for any award of any other degree or qualification in this or any other university or college of advanced education.

This thesis was written by me, Abdullah Aldawsari, and it was produced using Microsoft Office Word.

Abdullah Aldawsari

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Chapter 1:

Introduction

This chapter presents the following:

- An explanation of the research and the motivating factors for this study
- The research questions
- An overview of the research methodology
- An indication of the main contributions of this research study
- An outline of the thesis structure

1.1 Motivations

Society today is dependent on the daily use of cars and other private vehicles and the demand for them continues to increase. However, the increased use of such vehicles results in an increase in the number of fatalities caused by road accidents. The related costs and expenses, as well as personal tragedies, are reported to be a great concern that need to be resolved to make the roads safer and better for the drivers. Based on the report published by the Department for Transport (DFT), over 24,770 fatalities and injuries were caused by road accidents in the UK [1]. The statistics of road causalities send an alarming message to authorities and call for solid and robust actions to prevent such horrific situations on British roads [2]. Furthermore, these statistics highlights the fact that a considerable amount of damage to public property and loss of life takes place every year on the road, which must be dealt with by designing preventive strategies. Consequently, there is a continuing and urgent need to find solutions that may help to prevent road accidents and improve road safety.

In recent years, there has been a focus on road safety applications [2], [3] that use intelligent transportation systems (ITS), benefiting from wireless communications and mobile computing. A vehicle ad hoc network is regarded as the key part of ITS, which uses “dedicated short range communication (DSRC)” to facilitate communication between vehicles that are in close proximity. This development opens up the possibility of building a range of road safety systems and improvements; for example, accidents can be prevented by implementing sensors at intersections to avoid collisions, traffic signal violations can be monitored and lanes can be cleared for emergency vehicles [4], [5], [6].

However, it has been found that the majority of road accidents are caused by driver error [7]; a Department of Transport report found that in 2014, 26,496 accidents in the UK were due to drunk driving, reckless driving and tired drivers [7]. Technologies such as VANET are able to identify such behaviours, and they can be used to detect and prevent accidents caused by driver behaviour through the design of a more flexible and accurate detection system. The applications of wireless technologies and sensors devices can reduce the accidents on the road.

1.2 Aim of the study

The main aim of this research is to develop an approach based on the concept of context-awareness; this will be a system that accurately and proactively detects driver behaviour in particularly, the aggressive and reckless driver by taking into consideration the driver, the vehicle and the environment. Using this data the system will apply a behaviour detection algorithm within a context-aware architecture. Outputs will then be applied towards activating alarms within the vehicle, and issuing warnings to the driver or to other VANET components.

The sensing phase will collect data about the driver, the vehicle condition and the environmental changes. In the reasoning phase any uncertain and dynamic contextual data will be considered to determine driver behaviour status. This will be through utilising a Dynamic Bayesian Network (DBN) model to combine information from different kinds of sensors to deduce the driver’s current driving behaviour. The acting phase has the responsibility for alerting both the driver and others via wireless technology provided by VANET. As mentioned earlier, this study is focusing on the behaviour detection algorithm and the implementation of corrective actions within the acting phase will be left for future research.

1.3 Research Questions

The over-arching question for this research study is related to detecting abnormal driver behaviour within VANET using a context-aware systems approach. The research questions are:

- How can we design effective aggressive driver behaviour detection system architecture for VANET by employing a context-aware approach?
- How can the efficient and effective driver's detection system can be built which can do the reasoning under uncertain circumstances?
- What type of data is required to detect and predict various behaviours of drivers with great accuracy?
- How can we identify "Tafheet" which is the dangers common driving style in the Golf countries, and how can the system be applied in this dangers common driving style.

1.4 Assumptions

In order to achieve the aims and objectives of the current study, which are to develop a driving behaviour detection system to detect tafheet driving behaviour, are based on the following assumptions:

- The experimental vehicle is fitted with various monitoring and sensing devices such as a gyroscope, ESG and thin-film sensors.
- A global positioning system (GPS) and navigation system (NS) and digital map are present in each vehicle.
- The experimental road should be straight and clear.
- Each vehicle is fitted with an on-board unit (OBU) that works in a VANET environment.
- Each vehicle has the capacity to gather contextual information regarding the vehicle and environment with the help of built-in devices.
- The safety of the participants is the highest priority. The experimental vehicle should the meet the maximum requirements to ensure that it is as safe as possible.

The above mentioned assumptions are taken into account to interpret the results of this study as presented in chapter 7.

1.5 Research Methodology

This study utilises a constructive approach, denoting its focus on a new model and architecture. There are five phases and the first phase comprises a review of literature in this field. This was to gain background knowledge for the research and covered a variety of sources, including books, articles, and digital libraries. Three specific areas were researched, comprising context-aware systems, VANET, and current driver behaviour systems. Attention was paid to VANET architecture and applications, and wireless access technology in VANET. Several possible architectures were explored within the context and context-aware systems, and a detailed review was carried out on existing driver behaviour monitoring and detection systems; this included milestones and drawbacks.

The second phase investigates available reasoning techniques for normal and abnormal driver behaviour in order to define and infer behaviour. The technique applied to this study's detection model is then illustrated in detail. A third phase then designs the on-board unit architecture (OBU) to capture contextual data to deduce driver behaviour, leading to the fourth phase which combines information from different kinds of sensors. Several key network variables were used and various parameters were specified to maintain conditional independence. The final phase is the implementation and evaluation of the model using experimental and synthetic data; this presents case studies to test performance and show the system's ability for detection.

1.6 Success Criteria

- The success of the current work will be measured on the following criteria:
- The aim and research questions raised in the beginning of this study are met and addressed successfully.
- The applicability of the proposed architecture in VANET for detection of Tafheet, reckless and aggressive behaviours as exhibited by Saudi drivers during the course of driving.
- The reasons behind the choice of DBN model from other reasoning models was analysed; and evaluation of merits of this model was be performed for detection of Tafheet behaviour.
- The study has shown the uniqueness of the proposed driver detection model compared to other such models developed by other researchers.

1.7 Contributions to Knowledge

- This study offers several key contributions to knowledge. It presents on-board unit architecture for detecting the reckless and aggressive, and Tafheet driving behaviour. The components of the architecture were designed in such a way that they provide the detection of the Tafheet behaviour based on the sensory data. The DBN model for reasoning and the use of appropriate algorithms made it possible for the detection of drivers behaviour with lower intensity such as reckless and aggressive.
- It provides a new driver behaviour detection model taking into account temporal and static facets of driver’s behaviour; it is able to detect normal and Tafheet behaviour (reckless and aggressive drivers) and combines data from different sources to determine this accurately. This research has provided
- This research has furnished the driver detection system which can detect the driver behaviour in sequence from reckless to aggressive and from aggressive to Tafheet, based on the increasing severity of the driver’s behaviour. This is the unique quality of the proposed system as the previous driver’s detection system are only able to detect either reckless or aggressive driving behaviour in isolation.
- This research also improves the understanding of the complex human behaviour during driving on the road in a particular socio-cultural context of Saudi Arabia and other Middle Eastern countries., such as Tafheet behaviour of drivers. Tafheet behaviour is a dangerous behaviour involving the many actions from driver from behavioural changes to emotional changes along

with sudden and violent changes in the states and movements of vehicles. This proposed detection system takes into consideration of vehicles states drivers' states to detect Tafheet.

1.8 Outlines of Thesis

The thesis has been divided into the following chapters.

Chapter 2: Literature Review

This chapter gives the descriptions and explanations of the different components of communication within the proposed architecture and various VANET applications. The chapter also gives description of context-aware systems by defining context and explaining how to capture and model the context. It then shows how this proposed system differs from existing work.

Chapter 3: Preliminaries

In this chapter, an overview of driver's behaviour is provided with the definitions of normal, abnormal and tafheet behaviour with the reference to the proposed DBN driver's behaviour detection model. The second part focuses on the reasoning method (DBN) that is used to combine data from several sensors to infer driver behaviour. Finally, the third part introduces the GENIE software, which is the toolkit used to implement the proposed solution.

Chapter 4: On-Board Unit Architecture Based on a Context-aware System

This chapter describes the mechanism used for detecting Tafheet, aggressive and reckless driver behaviour in VANET. The on-board unit (OBU) is described along with the architecture that is based on a context-aware system.

Chapter 5: Preparation for Experimentation

This chapter introduces the experiment. It describes the cooperation between the author, the King Abdul-aziz City for Science and Technology (KACST) and the General Traffic Department (GTD), which was required to implement the experiment in Saudi Arabia and to provide volunteer participants that had previous criminal records in tafheet behaviour. The preparation took into account all safety requirements. It gathered the necessary information about the sensors and all the parts used in the test bed. It also selected the right vehicle for installing the proposed test bed, and considered all obstacles and difficulties that could be encountered throughout the experiment.

Chapter 6: Model of DBN for Driving Behaviour Detection

This chapter present eths model which is proposed to detect the drivers behaviour by applying a dynamic Bayesian network (DBN). A detailed description of each step is provided.

Chapter 7: System Evaluation and Case Studies

This chapter tests and validates the proposed model, explains how the system detects tafheet, aggressive and reckless driver behaviour by applying and combining all evidence to show the ability of the proposed system and how it detects various driver behaviours.

Chapter 8: Conclusion and Future Work

This chapter summarises the work presented in the thesis and draws conclusions. It then provides recommendations and suggestions for future research.

Chapter 2

Literature Review

This chapter presents the following:

- Present an overview of the MANET and the VANET
- The explanation of context-aware systems along with definition of context, reasoning and modelling of context used for reasoning
- Explore the existing detection systems used for drivers. Behaviour and the gaps in the research of drives' behaviour detection system

2.1 Introduction

In the present era of technology, the production and consumption of vehicles affect the life-style of society. This has filled the roads with vehicles, which has brought about the issue of road safety caused by the lack of attention by drivers, communication systems, safe distance between vehicles and irrational attitudes of drivers. These challenges have increased the number of incidences of vehicle crashes, road accidents and road fatalities every year. Such issues have prompted vehicle manufacturers and government agencies to join in eliminating these problems by designing the robust wireless access, wireless access for vehicular environment (WAVE). It not only has improved road safety but also has provided high-quality on-board entertainment and communication systems, such as internet access and games for drivers and passengers [17].

The vehicle ad hoc network (VANET) system is intended to provide vehicles with a self-organized wireless network that can be created and used on an as-needed basis. In order to enable the VANET system, an efficient routing system is required, which enables the transmission of packets from the source to the destination. For this purpose, vehicles need to be equipped with a wireless network, computerized control modules and transceivers that will transfer data between vehicles (nodes). However, the range of this network is limited to only a few hundred meters, which means that all vehicles on the road can communicate with each other through these nodes and that this communication can be extended by miles on the road by the simple flow of messages through these nodes, which establishes end-to-end communication.

VANETs are a part of mobile ad hoc networks (MANET) [18]. A major characteristic of

VANETs is the restricted mobility pattern caused by restricted traffic lanes and roads. The mobility and restrictions in mobility patterns are normally regulated by traffic rules and regulations. This mobility is discontinued in urban areas where the buildings and many traffic lights disrupt continuous communication patterns. Therefore, VANET is necessary to continue this communication by connecting vehicles. Vehicles moving on highways in the same direction at the same speed normally keep a fixed gap so that they can communicate with each other longer, compared to vehicles moving at changing speed and directions in VANET [19].

A routing protocol controls the communication between nodes, selects the next-hop nodes, distributes the information over the nodes and maintains the information flow in the form of packets to the target destination. This continuous flow of information occurs through routes containing many nodes in the network, which is governed by routing protocols. Although several routing protocols have been designed for MANETs, their mechanisms are not fit for the VANET because of the peculiar nature of VANET systems. VANET is a self-organizing decentralized system with restricted mobility patterns.

2.2 VANET Overview

VANET is regarded as a subset of MANET [18], which is a step towards the construction of an intelligent transportation system (ITS). VANET provides a good strategy to create a better environment on the roads for both drivers and passengers. This has equipped drivers with a sense of predictability regarding the situations and conditions on roads and the locations and directions of other vehicles on the road [20]. Thus, VANET is considered an effective approach to reducing the fatalities caused by road accidents. VANET also provides on-board entertainment because of the presence of various devices fitted in vehicles, which ensures connectivity with the internet. Wireless networks are provided so that passengers can use the internet experience and play games [21], [22]. Through VANET, vehicles can communicate with each other by establishing vehicle-to-vehicle (V2V) interaction. Vehicles can also interact with other through roadside infrastructures, such as road side units (RSU), thus forming vehicle-to-infrastructure (V2I) communication. Hence, the drivers can collect information regarding safe and non-safe conditions, such as traffic situations, traffic jams, collisions, weather forecasts, tourist information, warning messages and accident avoidance measures [21]. In addition, drivers can communicate through VANET with other vehicles about their location, direction and speed. This information helps drivers to take effective decisions about driving safely on the roads [23].

2.3 Vehicle Communication Categories

Vehicle communication categories fall into three major classes [24], as shown in Figure 2.1:

1. In-vehicle communication
2. Inter-vehicle communication
3. Vehicle-to-infrastructure communication

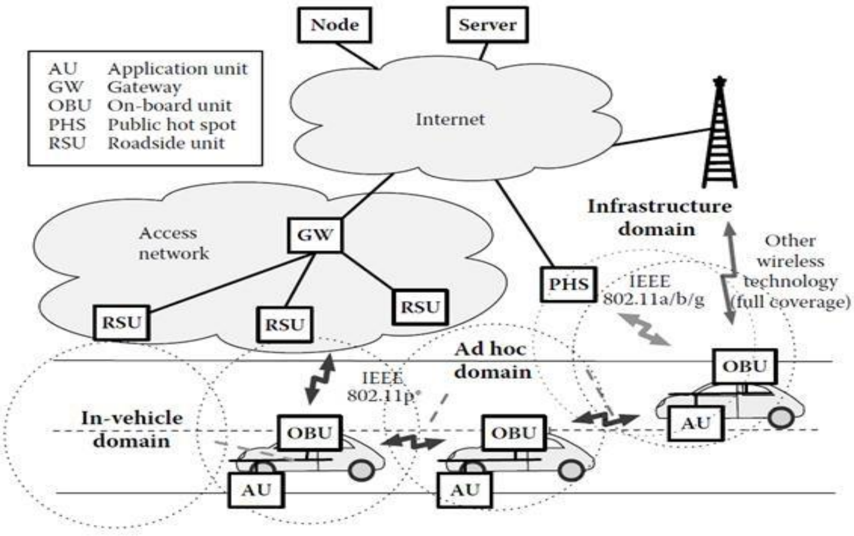

Figure 2.1: Different categories of communication in VANET [25]

2.3.1 In-vehicle communication (InVC)

In-vehicle communication (InVC) enables the interchange of information packets between application units (AU) and the On-Board Unit (OBU) employed in most of the cars run on roads. InVC can be divided into two categories. The first one is related to communication within the work of the sensors, actuators and controllers operating in the network of vehicular devices, and the second one is the communication of the multimedia devices used for the comfort of the passengers.

2.3.2 Inter-vehicle communication (IVC)

Researchers have focused attention on inter-vehicle communication because of its high importance in road safety measures and the need to enhance the visibility and predictability of drivers on the roads. The main purpose of this communication is to avoid road accidents and unpleasant occurrences on roads. Especially in the USA, Japan and the EU, this research is carried out through the collaboration of government agencies and the manufacturers of vehicles [27]. V2V communication forms the building blocks of IVC, which is managed in a decentralized fashion and permits vehicles to communicate with each other in the absence of infrastructure. Because of the high cost of the deployment of infrastructure on roads and the unavailability of infrastructure at all points on roads, IVC has gained tremendous importance for the researchers, manufacturers and government agencies working to reduce the number of accidents on roads [28]. Therefore, short-range microwaves are employed for the application of IVS. In the USA, the Federal Communication Commission (FCC) introduced the dedicated short range communication (DSRC), which uses a spectrum of about 75 MHz in 5.9 GHz band, whereas in the EU and Japan this spectrum is in the 5.8 GHz band [29].

2.3.3 Vehicle-to-infrastructure communication

The other name for vehicle-to-infrastructure communication (V2I) is road-to-vehicle communication (RVC), which is regarded as the most expensive form of communication because it involves the deployment of roadside units and base stations. These serve as coordinators among the subscribers to cellular networks. Base stations regulate the information between the road and the vehicles by establishing connections between the mobile vehicles and the roadside infrastructures [22]

2.4 Safety applications in VANET

In 2005, the U.S. Department of Transportation (U.S. DOT) reported [41] that the causalities and fatalities resulting from roadside accidents were increasing. This report triggered panic among government agencies and health organizations because of the billions of dollars spent on health and social care. In order to reduce the number of road accidents, vehicle manufacturers and government agencies began efforts to construct an intelligent transportation system [33, 44].

Consequently, DSRC was launched by the FCC in order to enable the vehicles on roads to communicate with each other. In the US, the range of this protocol is 5.9 GHz, while it is 5.8 GHz in the EU and Japan. Two kinds of communication are supported by DSRC: V2V enables vehicle-to-vehicle communication and V2I enables vehicles to communicate with BS and RSU. DSRC has seven channels, each of which has a coverage of 10 MHz (see section 2.9). Information pertaining to safety is gathered from sensors fitted in the vehicles.

In these applications, data are gathered, processed and disseminated to the vehicles moving in close proximity. This data can be forwarded through nodes in the case of V2V or transmitted to infrastructure through RSU and BS, as in case of V2I.

2.5 An overview of Context-Aware Systems

2.5.1 Context

The context has been defined by researchers in many ways. The origin of the word is from Latin: *con* means "with or together" and *texere* means "to weave". Thus, the word context suggests the creation of meaning from various factors in an environment [43].

Context was defined by [44] as a location and the people and objects around that location. [45] Provided a definition that included location, time, user identity and weather. The context was expanded by [46] to describe a user's emotional state. Context can be referred to as the information about an environment that is recognized by a computer or application [47]. It might also be considered an entity containing the particular factors that distinguish a current situation [48]. A narrower definition could refer to the information about the environment that is available to an application [49]. Furthermore, according to the online Free Dictionary, context is defined as “that which surrounds, and gives meaning to something else” [50]. Important aspects of context can include whom you are with, where you are in terms of location and the resources available to you [51]. In a broad definition, context is described as the physical, social or informational state of a user [46]. [52] provided a more accurate definition of context, which will be used in the current thesis: “Context is any information that can be used to characterize the situation of any entity. An entity is a person, or object that is considered relevant to the interaction between a user and application, including the user and the applications themselves.”

2.5.2 Context sensing

Context data is captured via various sensors, including hardware sensors and data sources that provide useful contextual information [53]. Sensors can be categorized as the following [54]:

2.5.2.1. Physical sensors. These sensors capture physical data [55], [56].

- **Light sensors:** Optical sensors include a colour sensor, IR or photodiode, which capture information about light density, reflections, and concentration and type of light.

- **Camera:** Camera sensors capture a wide range of visual information, and they are applied to processes such as object recognition.

• **Audio sensors:** Microphones capture audio information, including noise levels and different voice patterns, such as speech or singing, and they can be used for speech recognition.

• **Accelerometers:** These sensors gather data on the acceleration and movement relating to an object.

• **Location sensors:** These sensors provide location-related information. Two examples of are GPS and GSM. Some systems such as Active Badge determine whether a location is indoors or outdoors.

• **Touch sensors:** These sensors respond to the user's touch and are often used as energy saving devices and in various functions.

• **Temperature sensors:** These sensors measure temperature and weather applications.

• **Air pressure sensors:** These sensors evaluate pressure and altitude. The status of a vehicle's door (open, closed) can be shown by these sensors.

• **Motion detector (movement sensors):** These sensors detect the motion of objects.

• **Magnetic field:** This type of sensor detects magnetic fields and can be used in several applications, such as determining an object's direction and movements.

• **Biosensor:** These sensors detect biometric information. For example, they provide information about skin resistance, blood pressure, and so on.

• **Mechanical force sensors:** These sensors detect mechanical forces. For example, they determine weight, and they can be applied to determine if someone is sitting or holding a steering wheel.

• **Proximity sensors:** These sensors activate when a nearby object is located. Applications include waking from sleep mode or determining that an immediate environment is clear of objects.

• **Humidity:** These sensors detect humidity.

Physical sensors are available in a variety of formats, and they are able to capture various metrics. Utilizing a combination of various sensors allows capturing information in order to inform a context-aware system. The list of the commonly applied sensors in pervasive computing has been given by [56], as shown in Table 2.1:

Sensor type	Usage percentage
Movement	31%
Light	18%
Force	15%
Temperature	12%
Audio	12%
Humidity	6%
Proximity	6%

Table 2. 1: Common pervasive-computing sensor types

2.5.2.2. Virtual sensors: These sensors gather context data via various software applications. Examples include determining the location of a computer while the user is using a travel booking system or sending emails.

2.5.2.3. Logical sensors: These sensors utilize data from physical and virtual sensors and process them for solve complex problems. Examples include using a physical sensor such as a GPS and combining it with the current location of a user as determined by a virtual sensor in order to determine a user's exact location within a company.

The basic use of any context-aware system will include the gathering of contextual information. The approaches gathering this data can be further categorized as follows [53]:

- **Direct sensor access:** These sensors are built into devices and give data directly to the relevant software without other additional layers. A limitation of these sensors is their inability to provide data concurrently to several applications.
- **Middleware infrastructure:** This architecture provides a middle layer that encapsulates many functions, thus hiding many lower-level details. This separation of layers facilitates the reusability of the hardware sensors and the possibility of concurrent access by applications to the sensors.
- **Context server:** context serves allow the different users to gain access to the remotely located source of data simultaneously. This is done through a context server that gathers context data from sensors, centralizes it, and then offers the data to various users based on access rights.

2.5.3 **Context-aware systems (CAS)**

Context-aware systems (CAS) independently evaluate a current context and adapt certain operations based on that evaluation [53]. In 1994, context-aware computing was defined by [51] as software that behaves according to environmental information, such as by making adjustments based on location, people or objects in a context area. In the context of vehicles, the sensors fitted in the vehicles extract the information from the states of vehicles drivers and the environment of the vehicles, interpret the collected data and responds to the changes in the context [57. Subsequently, [58] added defined these systems utilise the sensors in vehicles to provide information or services to a drivers and passengers based on a current context.

Context aware system consists of simple sensors to multi-sensors depending on the nature of environments to be sensed. For vehicle context aware systems, the context aware systems are designed to sense the complex environment which is dynamic rather than static one. The environment, and vehicle and drivers exist in dynamic environment. Therefore, the multiple sensors are required to be embedded in the vehicle to capture the information of the environment, which is fused through the multi-sensor fusion features in order to interpret the accurate state of the system [49, 52].

For the purpose of fusion of sensory data and synthesis of logics to address the complexity of the system, the algorithms and different level of architectures are designed. The architecture may involve the different phases ranging from sensory phase through processing phase to the action phase [60, 61]. In order to develop the context aware system for the current research, the architecture of foregoing phases have been developed which will be discussed extensively in Chapter 4. Consequently, the context-aware systems are the integral part of a driver's behaviour detection system in complex and dynamic environment which the current research intends to sense for the detection of Tafheet behaviour.

2.5.4 Context-aware system architecture

Context-aware systems typically consist of three main subsystems [50]:

- **Sensing subsystem:** This subsystem is responsible for gathering context information throughout sensors.

- **Reasoning (thinking) subsystem:** This subsystem provides logic and reasoning techniques to interpret the contextual data and to facilitate a high-level context, such as the user's situation.

- **Acting subsystem:** This subsystem provides various functions and services to an end-user.

Several system architectures have been put forth for the design of context-aware systems. Figure 2.2 shows a three-layer architecture, which was proposed by [62].

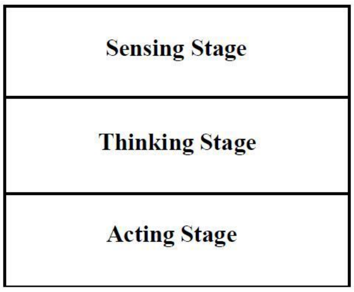

Figure 2.2: A three-phase architectures based on context-aware systems [53]

The three layers, which represent the main phases in the architecture, include sensing, reasoning and Action phases. The context-aware system of architecture contains three major context-aware sub-systems: sensing, reasoning and acting. For example, the third phase contains the alarms to alert the drivers, which collects the input data from the second phase, which in turn depends on the first phase for the input data to complete the task [53].

2.5.5 Context modelling and reasoning

Data gathered by sensors comprises information relating to the context and thus must be defined and stored in a context model. Various models have been developed for context modelling and reasoning, which are described below:

- **Key-value model:** This model is the very easy and simple form modelling a context. A simple pair called a key-value is used to define the attribute and a value. Examples include time, such as 12:00 a.m., name-David, or location-classroom 205. Key-value pairs are simple to manage and are frequently used. These key-value pairs, however, can be limiting in the development of complex context retrieval algorithms.

- **Mark-up scheme model:** In this model, mark-up tags provide attributes and content within a hierarchical data structure. The mark-up tag content is then recursively defined by other mark-up tags.

- **Graphical model:** The unified modelling language (UML) is a general-purpose modelling tool and includes a powerful graphical component. Because of the generic structure of this model, it is also suitable for modelling context. This modelling tool is often used to build an entity relationship model (ER-model) for a relational database system, which can be built as a management context system.

- **Object-oriented model:** It is used to describe context processing and serves as an access to the context information within an object. Furthermore, it facilitates interaction only through identified interfaces. This can be a very robust approach to development. It ensures reusability, especially in contexts that may change rapidly.

• **Logic-based model:** This model is defined by a high degree of formality because a context is captured in the form of logical rules, expressions or factual information. In logic, expressions are derived from a set of other expressions.

• **Ontology-based models:** This model provides tools to identify concepts and their interrelationships. As such, the models can be very expressive and capture many possibilities, which can be very appropriate for modelling the context. The *Context Broker Architecture (CoBrA) system* [63] is an example of an ontology-based model. This model characterizes entities, such as person and place, within a defined set of concepts.

Context data should be generated by an application available for use. For example, raw coordinates are supplied by a location sensor and passed on to an application. Raw data can be processed prior to use by an application [64]. Several requirements should be set to determine and properly model a context. The following requirements were proposed by [65]:

• **Heterogeneity:** The variegated sensors are used in the context modesl to sense the context.

• **Dependencies and relationships:** Determination of dependencies and relationships of the objects using the context aware concepts is another important feature of the context models.

- **Timeliness:** The context model work in temporal manner and collect the histories about the different contexts.

- **Imperfection:** The context models are always accurate in recording the contextual information because of the use of a variety of sensors**.**

- **Reasoning:** Another important characteristic of the context models is that they can process the data acquired from the sensors by supporting the functions of the different reasoning techniques. For instance, drivers' data provided by sensors can be processed and reasoning is performed on it to detect the behaviour of the drivers.

- **Usability:** The context models must be useful in terms of interpreting the data acquired from the different types of contexts so that reasonable action can be taken in response to the contextual information.

- **Efficient context provisioning:** The models developed to sense the context must be able to provide access to the all relevant information about the contexts under investigation.

One challenge that needs to be addressed is the provision of reasoning in the context of uncertain information [66]. The previous models described are not particularly well suited to execute this task. In general, they only capture, define and store certain types of context data, such as room specifics, light, weight, and so on because of their reasoning limitations. For example, ontology-based models have limited reasoning [65], [66]. Graphical models also do not provision for reasoning [67].

High-level context information should also be considered. This kind of context can be seen in various activities, such as if a person is not moving, he or she might be sleeping; or if a car is moving, it may be driven normally. This kind of conclusion cannot be captured directly by a sensor, and it may involve information that is dynamic, incomplete or inexact. For example, a system may need to judge whether a person is driving and alert or is affected by fatigue or alcohol. This kind of conclusion cannot be necessarily derived from simple or low-level information, such as vehicle speed, direction or angle of motion [68], [69], [70], [71]. Moreover, context information often includes a degree of uncertainty [66], [72], [73] and may require the application of reasoning.

Reasoning provides the ability to utilize acquired context data from sensors in order to determine a higher-level context. Collecting high-level information from a combination of low-level sensor data, however, can be a significant challenge. Several reasoning techniques have been put forth [65], [66], [74], [75], [76]:

- **Fuzzy logic:** This logic is used to process the contextual data provided by the sensors embedded in the contextual model. It has been utilized in the context aware systems designed to identify the complexities of the context. The information collected and processed by fuzzy logic and the outcome is shown in the form of binary digits (0, 1) which means that either is state determined is true or false. Fuzzy logic takes a different approach. Instead of trying to assign a binary determination, it will come up with the probability of an occurrence. For example, will occur, probably will occur, may occur or may not occur. One of its aims is the development of a methodology for the formulation and solution of problems that are too complex or too ill defined to be analysed by conventional approaches.

Fuzzy logic is suited to combining information from multiple sensors and to resolving subjective contexts. Two or more fuzzy sets can also be combined to acquire a new fuzzy set. However, fuzzy logic may not be effective with inaccurate and incomplete data [77].

• **Probabilistic logic:** This approach puts forth a logical assertion that is associated with a probability. This results in statements such as “The probability of D is more than 1/4” and “The probability of A is F is at least triple the probability of B”. The letters A, D and F represent the random variables and allow the users to infer the probable states of the contexts in terms of their strong probability to occur under a particular set of conditions. This results in the deduction of high-level data showing the probable contextual information. For example, based on these rules, a Prolog engine can be employed as a reasoning instrument [78]. Probabilistic logic, however, is unable to furnish the necessary relationships of the variables in the uncertain contextual information., which makes it difficult to use in dynamic situations [79].

• **Neural networks:** This approach attempts to mimic how the human brain works. Hence, a network of interconnected entities called neurons performs parallel and non-linear functions through these neurons or processing units. These systems typically have been used to map a large amount of data to a smaller number of outputs [80], [81], [82]. Some limitations to this approach include determining network architecture, and prediction seems less robust than in some other techniques, such as Bayesian networks [83]. Training a neural network can also be very time consuming [84].

• **Hidden Markov models (HMM):** This models offers the representations of different states which the system detects and the ability of states from transition to other states. The model's states are hidden and cannot be observed directly. Different set of signals are obtained from the each state, which makes possible to distinguish it from the other states. HMM is a sub-set of DBN [85], [86]. Distinction of DBN from HMM is that it contains hidden variables in the form of different random variables which are representative of that state. The difference between them is that DBN represents the hidden state in term of a set of random variables, whereas HMM represents the "hidden state" in terms of random single variable. In addition, the graphical presentation in DBN is more general compared to HMM. [87].

• **Bayesian networks (BN):** These appear in the form of directed acyclic graphs in which different random events are represented by nodes, and the relationships between nodes (parent nodes and child nodes) are represented by arrows. They are very useful instruments in terms of delivering uncertain contextual information efficiently. They are unique in that they provide stand-alone reasoning, such as the derivation of outcomes from the root causes and vice versa. BNs are also known as efficient means of deducing high-level context information by using inference methods from low-level contextual data. BNs are normally characterized by single invariant slices of time over which the beliefs and evidence can be applied and supported, which means that these types of networks are not suitable for time scales undergoing variations. [9], [66], [78], [79], [88].

• **Dynamic Bayesian networks (DBN):** These networks are a subset of static BNs, which are structured by combining different time slices in a sequential manner. A hidden Markov model (HMM) can be used to model the relationships between two adjacent time slices. DBNs are general forms of HMM in which a set of random variables characterizes a peculiar state, instead of using a single random variable. In contrast to static BNs, they characterize the current context by taking the readings of sensors from the previous time slice (the random variables at time slice t with the state at time (t-1)) [9], [11], [86], [89].

For example, driver behaviour is pinpointed as high-level behaviour, and the information derived from various sensors in the vehicle needs to be combined in order to anticipate the driver behaviour in the current time slice. The drivers might exhibit different discrete behaviours at various time scales, so the correct modelling of driver behaviour requires the combination of all behaviours shown at various time scales in order to characterize this particular context. Furthermore, because the modelling of driver’s behaviour depends on the sensor readings, which might be incorrect, the uncertainty and randomness are inherent in this process. In order to minimize the impact of this uncertainty, the combination of all variables is vital for modelling the driver’s behavioural context. Researchers have applied different methods to combining the sensory data, which carry their own pros and cons.

2.5.6 Justification of choice of DBN over other representations

The current research applied DBNs in combining sensory data for the deduction of driver's behaviour, based on the following reasons:

• The ability to process the static and temporal data form the domains in the model, especially the events which are subject to changes with the passage of time [9], [11], [79], [88], [90], [91]

• Provision of a framework in which various levels of abstraction can be used to infer data (e.g., multiple contexts from different kinds of sensors) [9], [79], [92]

• It minimises factors of uncertainty and randomness to a considerable extent [9], [65], [76], [79], [88]

• Efficiency in deriving uncertain data from sensors and combing it to find inferences to high-level contextual information [73], [88], [90], [93]

• The ability to blend data efficiently from both current and previous time slices [79], [84], [88], [90], [94]

• The availability of efficient algorithms for both inference and learning purposes [88], [90], [92], [93]

- It has the ability to combine the datasets and expert knowledge [90], [94]
- Its functions with a great deal of accuracy compared to other models in terms of a choice of best next action or decision [92], [93].

- In contrast to other models it also provides the option to the user to fill out the missing values and perform inference from low-level contextual information to a high level contextual information [65], [76].

2.6 Overview of Statistics on Road Causalities in the UK and the KSA

Since 1991, the Department for Transport (DFT) in the UK has published reports and articles about road casualties resulting from road accidents caused by abnormal driving behaviors. Based on the report published in 2011, road causalities due to heavy drinking, aggressive and reckless driving behaviors of the vehicle drivers constituted the major proportion of deaths, which were evident from hospital admission data generated from the road accidents and police reports [95].

DFT also reported several contributory factors to road casualties, such as inexperienced drivers, injudicious action (mobile use during driving), aggressive, reckless and fatigued behaviors of the drivers while driving vehicles on roads in the UK. The injudicious actions, aggressive and reckless actions and inexperienced drivers were considered the second most important category of contributory factors, having caused 24% of the road casualties and accidents (see Figure 2.3). The injudicious actions and inexperienced drivers were responsible for 28% and 27% of the road fatal accidents, respectively [1].

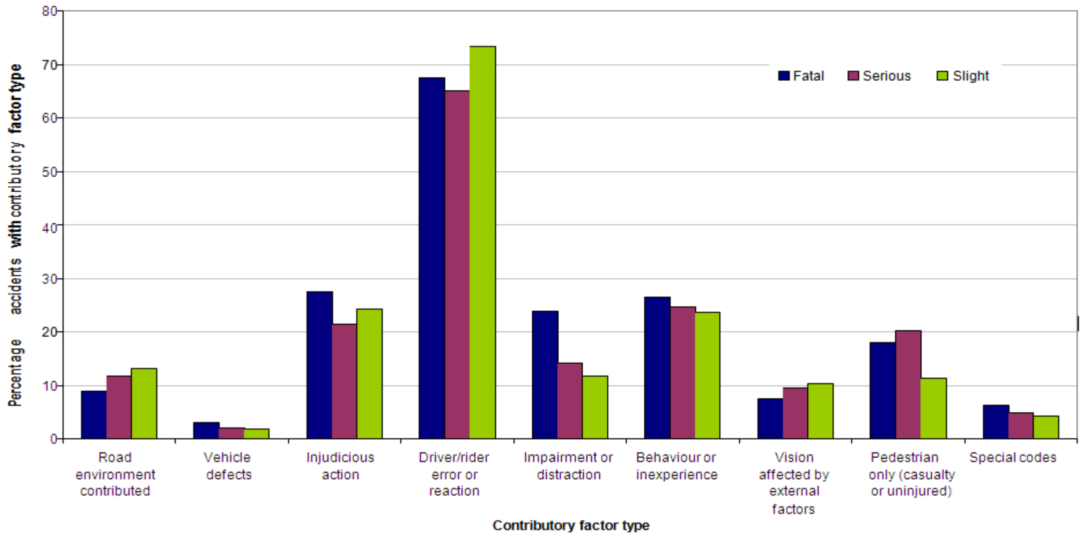

Figure 2.3: Contributory factor type [1]

- The total number of casualties in 2011 was 203.950, which was 2% lower than in 2010; and 1.901 were killed, which was a 3% increase over 2010.
- The total value of prevention in 2011 was £15.6 billion.
- The contributory factor loss of control contributed to 34% of fatal accidents.
- Exceeding the speed limit and travelling too fast contributed to 25% of fatal accidents.
- Injudicious action and behaviour/inexperience contributed to 28% of fatal accidents.

  - Most fatalities resulting from car and motorcycle accidents included users within age range 17-50.
- Nearly one-fifth of all car occupants killed or seriously injured were young car drivers.

- 19% of adult drivers who had taken illegal drugs contributed to road accidents in 2011.

The reasons for these road accidents and causalities were related to the lack of education and the presence of gaps in the regulation of traffic on the road, as suggested by Dr Jillian Anabel in her famous lecture, “More Haste, Less Speed”. She argued that the UK government is much too focused on the development of regulations and that less focus has been placed on changing the behaviour of vehicle drivers through concerted counter-measures and education plans. The application of both education and regulations to change the behaviours of vehicle drivers has proved to be an effective and efficient approach to tackling road accidents, although it may not be welcomed warmly by the “World of Nudge” [96].

Similar problems have been faced by governmental authorities in developing countries, where the situation of both regulations and education is even worse than in the UK. For instance, Saudi Arabia is reported to be one of the countries with unsafe and dangerous roads, which is partly because of poor regulations and their implementation in road traffic and partly because of the lack of education for drivers regarding how to drive on roads and consider safety measures during the driving process. According to report published in 2008, the rate of road casualties amounted to 18 persons/day [97], [98]. The contributory factors to road accidents and casualties were published by the Saudi Interior Ministry, which showed that abnormal driving behaviours caused 54% of road casualties, while road conditions and bad weather resulted in 3% of road accidents and subsequent road casualties. Similarly, vehicle anomalies constituted 54% of road accidents.

According to a report published by MCBI, "*in 2014 Saudi Arabia spend more than £3 billion in the road causalities 90% of the accident caused by the vehicles derives*" [99].

2.7 Driving Behaviour

In order to define the concept of driving behaviour, it is appropriate to explain the differences between the driver performance and the driver behaviour.

The driver's performance is usually measured by various methods, such as the assessment of driving skills, traffic and road knowledge and cognitive abilities of drivers. However, the driver's behaviour is related to actions executed by the driver in the actual sense while driving the vehicle on the road. Hence, the methods used to assess the driver's performance are inapplicable to the qualification of the driver's behaviour. Consequently, academics and researchers face a great dilemma in establishing relationships between the driver's actual actions and performance mainly because of the lack of quantification strategies for the actions/behaviours of the driver [100].

In order to tackle these challenges, researchers have adopted a two-pronged approach that involves internal and external views. The external view approach requires the collection of data about the external environment of the vehicle by using various instruments and observers and recorders to gauge continuously the external environment of the driver. These data help researchers to develop a broad picture of external factors that influence the drivers' actions. On the other hand, the internal view approach involves the observations and records of the drivers' internal conditions, such as emotions, thoughts, physical conditions and feelings. The measurement of these variables cannot be taken by any available instrument. Because of the complexity arising from the changing patterns of human behaviour, researchers are continuously engaged in detecting the various behavioural patterns of the driver and in developing models and systems that could perform corrective actions on the abnormal behaviours of the driver.

Modern psychology is used to explain human behaviour. Perceptions, thoughts, feelings and willingness are brought under the umbrella of human capacities, which psychologists define as behaviours. For example, the perception of light or the failure to perceive it and feeling angry and intending revenge are different forms of behaviour. When people are engaged in a special activity in groups, then their behaviours are described with reference to the groups in which the behaviour takes place. Examples of such behaviours are sexual behaviour, smoking behaviour, food behaviour, crime behaviour and driving behaviour.

Both ancient philosophers and modern psychologists have described human behaviour a obeying a three-fold system: will, understanding and action. The behaviour related to the will of an individual can be described generally as “affective behaviour”, which includes emotions, feelings, needs, motives, affections and resolutions. For instance, displaying a signal before changing road lanes while driving on the road is categorized as an affective behaviour. Similarly, the avoidance of driving errors is also related to an affective motive. When the driver obeys these affective motives, the chances of driving errors can be minimized. However, when the driver is in rush or hurry, the desire to obey affective motives is weakened by the “overriding will” to reach the destination before a set target. This overriding urge to hurry leads to driving errors, resulting in road accidents and mediated by abnormal affective behaviour. This explains the role of affective motives in mediating the driver's erroneous behaviour. Thus, any theory of driving must take into account these motives and needs in order to explain affective driving skills and errors [101].

The observation of the three-fold system of behaviour is important to detect the abnormal motives and factors leading to road accidents. A major proportion of road accidents are caused by the lack of decision making power while driving on the road. Accounts of road causalities caused by such abnormal behaviour are quite lengthy. According to the statistics published by UK authorities in 2011, the number of human road causalities was 203,950. The continuous trend in the increasing number of road casualties since 2003 was described in the same report. The DFT attributed several factors to the increasing trend of deaths caused by road accidents, such as drinking heavily, driving recklessly and aggressively and so on [96].

2.8 Driver Behaviour Detection and Monitoring Systems

Previous researchers have applied several systems and methods in order to develop systems that monitor and detect driver's behaviour by relying on different methodologies. Without taking the state of the vehicle into account, some researchers have attempted to detect and measure the state of the driver in the vehicle, such as drowsiness, exhaustion or drunkenness. However, some Researchers have tried to detect the driver's behaviour by combining the data from the driver, the vehicle and the surrounding environment, as shown in Figure 2.4. The merits and demerits of each category are discussed separately in the following section.

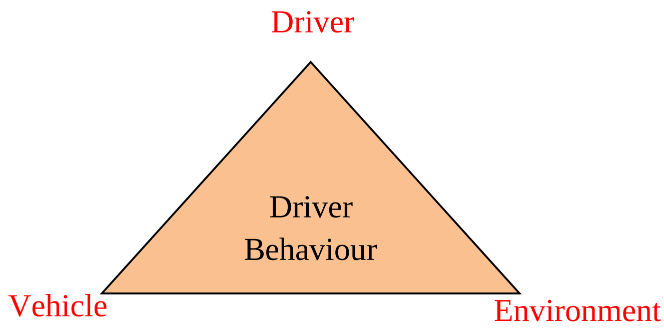

Figure 2.4: The main factors in driver behaviour monitoring and detection systems

2.8.1 The process to monitor the entities (environment, vehicle and the driver)

A hierarchical model was employed to design a context-aware smart car was built by [12] which was capable to perform reasoning over the collected data and to suggest the possible solutions in response to contextual information associated with vehicle and driver for making the journey comfortable for passengers travelling on the road.

The smart car's general architecture was developed to collect contextual information about traffic conditions (e.g., relative velocity), driver status (e.g., driver's gaze) and vehicle parameters (e.g., normal operation). This information can be used by the smart car to assess risk and to warn the drivers to modify their behaviours accordingly to avoid an unpleasant event. This context model classified contextual information

The model determines the semantics and places them in different layers, for instance, the sensor layer provides the contextual information while the situational layer assesses the probability of the scenarios with assignment of suitable values of probabilities. The patterns of the events are derived from the time-series of data and reasoned upon them to conclude the possible reaction.

The contextual layer contains the information about the different contexts such as the information regarding the weather, the nearest gas station, the drivers (aggressive or reckless), the state of temperature and humidity and states of the car's engine and motion of vehicles. These data are collected by applying the ontology method. The information this collected is passed on to the situational layer in which the high-level contextual information is derived, which is used for decision making purpose of the system. This is done through the application of Petri net.

A smart car software platform consisting of four layers was developed, as shown in Figure 2.5:

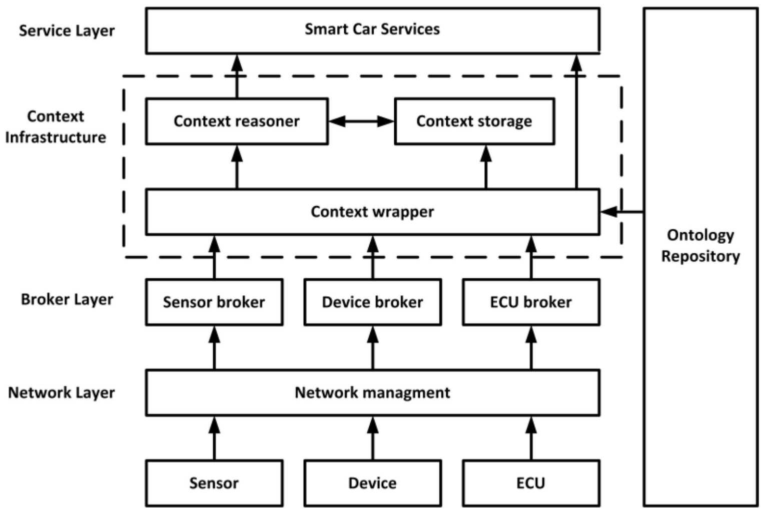

Figure 2.5: Software platform for a smart car [12]

- **Network layer:** This layer connects all the devices required for the proper functioning of the system.

• **Broker layer:** This layers is important for discovering and logging in the new sensors being added to the system.

• **Contextual infrastructure:** The context infrastructure contains three parts: a context wrapper transforms sensor data into semantic context atom; a context reasoner provides training data regarding the different situation tools for their identification.

• **Service layer:** This layers executes the actions suggested by the model, for instance, car can be slowed due to emergency situation ahead or bad weather.

In this system, the driver's state is considered an uncertain situation, and it is dealt in the situation layer by carrying out the information fusion process. However, the temporal aspects of driver's behaviour are not taken into account by this system, which constitutes very important segment of information and evolves over time. This system only detects the driver's context by capturing the movement of his or her eyes, which possibly leads to the collection of inaccurate information regarding the driver's actual state or behaviour in the vehicle.

The tolerant context-aware driver assistance system (TOCADAS) was designed by [102] for reduction of fatalities on road through accidents, which works on the principle of detection of drivers' behaviour and provision of suitable service accordingly to them to avoid unpleasant incident.

Their context model is suggested by [12], which consists of sensory layer responsible for sensing the different contexts, the contextual layers responsible for identifying the real world from the abstract world. And the situational layer responsible for processing the complex data and deduce the possible solutions to resolve the complexities.

Fuzzy membership functions are utilized by this system to map the acquired contextual information and convert it into linguistic variables that further assist in the construction of a linguistic information system. Association rules are then applied based on a rough set to extract the control rules for the system from a linguistic information system. Hence, this system collects temporal information regarding vehicle and driver in order to detect an accurate temporal pattern. Following these patterns, the services are provided to the driver based on his or her current behaviour. The focus of this system is to provide the right service to the driver at the appropriate time based on his or her current behavioural situation. The situation of the driver is characterized based on his or her interactions with the immediate environment, which includes the information related to outside temperature, brake signal, acceleration of the vehicle and wheel fraction. An inherent drawback in this type of system is the possibility of inaccurately monitoring the driver’s behaviour.

2.8.2 Summary of related driver behaviour systems

The erroneous behaviours of drivers are critical factors that contribute to road accidents. Most negative behaviour states can be detected by the detection systems developed by various researchers. The following paragraphs summarize the main research conducted in this area see Table 2.2 below.

The research work of [103] aimed to determine the drivers’ intentions in the driving context by estimating the current manoeuvres according to the information generated by the devices and sensors installed in the vehicle. For this purpose, they developed an intelligent driving recognition with expert system (IDRES) to build an experimental vehicle containing state-of-the-art sensors and software for the determination and analysis of driving situations and drivers' manoeuvres. Therefore, this project was of commercial importance. They used the rule-based system to construct IDRES, which is a double level, rule-based system with two decision levels: advice and sequence recognition. The first level receives the data from the sensors and processes driving situations, whereas the second level is involved in the recognition of the manoeuvres performed by drivers corresponding to these driving contexts. The reliability of the measured manoeuvres was improved by using the Dempster–Shafer theory. Hence, the proposed system was able to recognize the manoeuvres carried out by the drivers, followed by the evaluation of the confidence in and reliability of these recognitions.

Similarly, [104] developed an experimental vehicle equipped with several sensors and data acquisition devises—the "SmartCar tested". Their experimental goal was to develop a comprehensive theoretical learning framework for modelling driver's behaviour and recognizing the manoeuvres of drivers in a dynamic driving context by using a real-time data acquisition system. They modelled seven various driving manoeuvres: starting, stopping, turning right and left, changing lanes right and left. They used different modelling techniques, such as graphical models, the hidden Markov model (HMM) and its extension, the coupled hidden Markov model (CHMM). They used different sensors in the SmartCar to record data related to the driver's context, such as cameras to view the car's internal state, surrounding lanes and traffic, the driver's face and head movements.

The output signals were received through a video Walkman VCR. This research work aimed to provide leverage to the car industry in building a smart car that could sense the driver's manoeuvres with one-second accuracy before they took place.

Similarly, [105] aimed to model driver behaviour by using the HMM as a modelling technique. The aims of this research were to predict the behaviours of the driver and to build an adaptive assistance system based on interpretations of the driver's behaviour. In order to build an adaptive assistance system in real time, the vehicle was supplied with sensor cameras on the front and rear and within the vehicle. The data received through these sensors was interpreted by using HMM. A prediction about driver behaviour was made to assist the drivers in avoiding any dangerous situation on the road. This work was carried out for academic purposes.

Some researchers also attempted to determine driving patterns and their classification. For instance, [106] aimed to classify of driving patterns originating in the vehicle's characteristics during driving, such as acceleration, usage of neutral networks, deceleration and turning of vehicle. They applied the neutral-networks technique to model behaviour. Two important sensors, the accelerometer and the GPS receiver, were utilized in order to derive input data to draw the output driving features described earlier. This approach was adopted because the GPS data derived from the accelerations proved sufficient to describe all semantics of driving behaviour. This research work was carried out for academic purposes.

Another research work conducted by [107] evaluated the comfort and ease of a public transportation system by using the embedded sensor system. Three algorithms were used as modelling technique. The threshold detection algorithm measured, analysed and compared the acceleration peaks with the threshold acceleration peak values that caused by rash driving behaviours, such as reckless driving, holes and bumps on the road. The jerk detection algorithm detected the changes resulting from the acceleration changes and jerks. The rate monotonic scheduling (RMS) algorithm measured the frequency-weighted accelerations according to the ISO2631-1 standard. The embedded sensor system was comprised of different sensors, including GPS, accelerometers and temperature sensors aided by wireless communications. This academic research showed the time, magnitude and geographic position of events in a LabView interface with the help of the online Google Map system.

[108] conducted an academic research project that proposed a behaviour modelling system for recording driving events and detecting unsafe driving behaviour. The goals of the system were achieved by the application of different sensors: a tri-axial accelerometer and an engine control unit, as well as a camera used to view the driver's perspective, the passengers and the car. Thus, the detection of a hazardous event was achieved by combining the output from these sensors with a fuzzy interference system by using the fuzzy logic modelling technique.

Another research group [109] from the Microsoft Research Industry of India developed the Nericell system, which is specialized for the rich monitoring of road and traffic conditions by using mobile smart phones. Nericell was able to perform rich-sensing tasks by exploiting the facilities and services of smart phones carried by the user while driving. Nericell detected bumps, potholes, honking and braking with the aid of data collected by the sensing devices of an accelerometer, microphone, GSM radio and GPS. The threshold detection technique was used as a behaviour modelling technique for the analysis and interpretation of the data retrieved from the sensors. Because this system does not involve expensive vehicular or roadside sensors, it is efficient and cost-effective.

Similarly, [110] conducted an academic research project that aimed to understand driver behaviour by using smart phone sensors, such as an accelerometer (acceleration and deceleration), a gyroscope to detect deflection angle-related sensory information, and a magnetometer to measure magnitude. Endpoint detection, Bayesian classification and dynamic time warping (DTW) algorithms were used as behaviour modelling techniques to analyse driver behaviour.

A similar approach was adopted by [111] to investigate whether the driver's behaviour on the road was typical, non-aggressive or aggressive by using a smart phone as a sensor platform. They applied the modelling technique to the data analysis, including the dynamic time warping (DTW) algorithm and the Bayesian classification algorithm as behaviour modelling techniques. Moreover, this system used smart-phone based sensors, such as the magnetometer, gyroscope, accelerometer and GPS, to detect, recognize and record of events. Processing was accomplished within a smart-phone without external processing devices. This smart phone-based driving style recognition project was of academic importance.

[112] carried out an academic research project that presented two models, each carrying a combined capacity of acceleration and speed data in a driving detection system. The aim of their research work was to reduce the number of road fatalities by devising an

innovative approach to monitoring driver behaviour in real-life situations by considering various vehicular and road dynamics, including passenger comfort, road infrastructure and design and vehicle dynamics. Through their models, they successfully detected reckless driving behaviour by using the minibus taxi as an experimental vehicle.

Similarly, [113] endeavoured to develop a robust, non-intrusive and novel driver behaviour detection system by utilizing context-aware VANET with wireless access technology that was built into the in-vehicular environment. The major aim of the research was to detect the abnormal behaviour of drivers through the sensors present in the vehicular environment and to disseminate warning messages to the vehicles in close proximity to avoid road accidents and reduce the number of road fatalities. They proposed a context-aware architecture consisting of five layers and three phases in terms of its functionality in the detection of diver’s behaviour in VANET. It was able to detect four types of behaviours, drowsy, aggressive, normal and fatigued, and to send warning messages to vehicles in the vicinity to alert their drivers to perform corrective actions in order to avoid fatalities. The functions of the architecture were divided into three phases: sensing through the in-vehicular sensors; reasoning by using dynamic Bayesian networks about uncertain and high-level contextual information regarding the driver’s behaviours, and actions by sending the alert messages to nearby vehicles on the road. They used various types of sensors to collect data on the vehicle environment and driver behaviour: an internal set of sensors, which included a GPS, eye camera, accelerometer, speed sensor, lane camera and alcohol sensor, – to capture data from the vehicular environment; and an external sensor layer containing traffic management centres (TMC) and information regarding the other vehicles (Hello Messages). This academic research proposed models for industrial use in building robust safety applications for vehicles in order to avoid road accidents.

[114] aimed to develop a prototype driver behaviour tracking system for Aviva, a motor insurance company. Aviva gave the researchers the task of developing an efficient system that could track abnormal driver behaviour and penalize these drivers by increasing their insurance premiums. Aviva required this system because every year, the company dispensed massive payments for damages claimed by young customers because of their reckless driving behaviour. The researchers developed the telematics dashboard system to track driver behaviour by using different sensors, such as the accelerometer and the position and brake sensors. The sensors showed the information through acceleration gauge, the cornering gauge and the braking gauge if abnormalities in acceleration, cornering and breaking were caused young drivers. The system used Google Chart 2014 to improve the visualization features. This also presented tips to drivers to improve their driving score if they were lagging in any area of driving, such as acceleration, braking or cornering. The researchers undertook this project for commercial purposes requested by Aviva plc.

Ref	Aims of the modelling systems	Given Information	The modelling technique	Sensors used	Driver status	The purpose of the research
[103]	recognise driver manoeuvres from data sensors	driver manoeuvres	rule based	Camera	Driver behaviour Observer	Commercial
[104]	machine learning framework for modelling and recognizing driver manoeuvres	driver manoeuvres, speed, acceleration, vehicle heading	graphical models, HMMs and CHMMs	Accelerometer, speedometer, acceleration throttle, brake pedal and steering wheel	Driver behaviour Observer	Commercial
[105]	adaptive assistance system to determine/predict drivers' behaviour	driver manoeuvres, speed, acceleration, vehicle heading	HMM	Camera, speedometer, acceleration throttle, brake pedal and steering wheel	Driver behaviour Observer	Academic
[106]	classify driving patterns using neural networks	Acceleration and vehicle heading	neural networks	Accelerometer and GPS	all semantics of driving behaviour	Academic
[107]	evaluate the comfort in public transportation	Acceleration, speed and vehicle heading	three algorithms: Threshold detection, jerk detection and Comfort index measurement	Accelerometer and GPS	Reckless	Academic
[108]	record driving events and detect unsafe driving behaviours	View the drivers, speed and accelerometer	Fuzzy Logic	GPS, camera and CAN-bus reader	Unsafe driving behaviour (Aggressive)	Academic
[109]	monitor road and traffic conditions using mobile Smartphones	Speed , accelerometer, vehicle heading	threshold detection	Accelerometer, GPS and GSM module	Driver behaviour Observer	Commercial
[110]	understand the driver behaviour using Smartphone sensors	acceleration, deceleration, vehicle angle	endpoint detection, DTW, Bayesian classification	Accelerometer, gyroscope, magnetometer and GPS	Driver behaviour Observer	Academic
[111]	investigate driver behaviour as safe or unsafe	acceleration, deceleration and speed	DTW, Bayesian classification	Gyroscope, magnetometer and GPS	Aggressive	Academic
[112]	reduce the road fatalities by devising an innovative approach for monitoring driving behaviour in real-life situation	Speed and acceleration	two models that combine acceleration and speed into an erratic driving detection system	Accelerometer and GPS	Reckless	Academic
[113]	detect the abnormal behaviour of drivers	Driver head Position, Breath and eyes state.	dynamic Bayesian networks	GPS, camera, Accelerometer and alcohol sensor	Fatigue, Drunk, Reckless and abnormal	Academic
[114]	develop a prototype driver behaviour tracking system	accelerometer and driver position	--	acceleration and brake pedal	abnormal behaviour	Commercial

Table 2. 2 : A summary of Aims of the modelling, modelling technique, Sensors used and the purpose of the research

2.9 Summary

This chapter gives the explanations about VANET context-aware systems and an overview of the main techniques used to model and reason certain and uncertain contexts were explained, as well as the reasons DBN was chosen as the reasoning technique used in this thesis. The work that has been carried out in the driver's behaviour detection system has been classified in this chapter. This was discussed in order to provide background for the main idea and the mechanism of each system. Illustrations of the main associated drawbacks of each previous system were provided. Finally, the major difference between this work and previous works conducted in the field of detection of driving behaviour is that the present study aims to detect a unique, complex driving behaviour—tafheet —by taking into account factors that have not been considered by previous researchers in the Middle Eastern countries. Hence, this work is highly important in terms of increasing the accuracy and efficiency of a system used to detect drivers' behaviour.

Chapter 3

Preliminaries

This chapter presents the following:

- The objective of the driver behaviour (tafheet) detection system
- An outline and classification of driver behaviour
- The characteristics and features of Bayesian networks (BNs) and dynamic Bayesian networks (DBNs)
- An overview of the currently available DBN software
- The validation of the usage of GeNIe version 2.0 software

3.1 Introduction

In this chapter, the major concept that is elaborated and presented is the detection of the abnormal behaviour of tafheet (i.e., reckless and aggressive behaviour) by gaining information about the vehicle, the driver and the surrounding environment. Subsequently, a reasoning process is conducted to obtain corrective decisions that are issued to the drivers of the vehicles in the vicinity to prevent accidents on the road. Most previous studies conducted in this area considered only the data from either the driver and the vehicle or the vehicle and the environment. Moreover, they utilised a diverse array of reasoning methodologies. Furthermore, the driver's behaviour while driving is not a static and simple process. Instead, it is a dynamic and complex process that continues to evolve over time because of the interaction between the driver, the vehicle and the environment. Therefore, the driver's behaviour is not a certain entity, and any attempt to measure the behaviour of driver based on this assumption will lead to inaccurate results. Similarly, the information captured about the driver or the vehicle in isolation will result in the inaccurate detection of the driver's behaviour. Because of the complexity of a driver's behaviour, a comprehensive detection system is required to determine all aspects of abnormal behaviour in different contexts.

This thesis focuses on developing a novel behaviour detection system in which the driver's behaviour is considered uncertain, and both temporal and static aspects of driver's behaviour are measured. Based on the assumption of uncertainty related to the behaviour, the probabilistic inference is performed by utilising the DBN technique. The behaviour detection system is able to measure tafheet behaviour with greater accuracy by capturing information about various contexts related to the driver, such as heat pulse, grip and force. The system is also able to detect vehicle-related contexts, such as acceleration, vehicle speed, direction, the lane position of vehicle, and environment-related data, such as weather, noise, time, time zone and so on.

This research developed a novel OBU architecture for the detection of driver's abnormal behaviour by utilizing the proposed technique and the concept of the context-aware system, which consists of three layers: sensing, Processing and thinking layer and action. This architecture will be able to measure abnormal behaviour by capturing information about different states of the driver, the vehicle and the environment, as well as by performing reasoning about the collected information and finally applying the inferred decisions. The entire scheme of the proposed architecture and the functions of its various components will be presented in Chapter 4. In this chapter, the definitions of normal and abnormal driver behaviour will be presented. Moreover, the requirements and parameters for implementing the proposed detection system for the detection of reckless, aggressive tafheet behaviour will be elaborated. This chapter will also describe an overview of mathematical models, including BNs and DBNs. Moreover, the major steps in developing DBN involving inference algorithms are illustrated. An overview of different software packages applied to implement and evaluate the DBNs is also presented in this chapter.

3.2 Overview of Driver's Behaviour

A plethora of definitions and explanations has been presented in the literature about drivers' behaviour. Before embarking on detailed discussion about the behaviour of driver, it seems appropriate to define the act of driving. Driving is defined as the constant engagement of the driver with the vehicle and the environment during the movement of vehicle on the road [104], [115], [116]. The behaviour of the driver is characterized by the series of events and actions taking place during driving, each of which is initiated by a specific situation and contextual information about the vehicle, the driver and the environment [116]. The behaviour of the driver is also defined by its relevance to the other entities in the surrounding environment. In this study, it is assumed that if the driver's actions do not cause any harm to the relevant entities on the road, his or her behaviour can be characterized as safe or normal. However, if these actions lead to accidental situations on the road, then the driver's behaviour is labelled as unsafe or abnormal.

If the driver behaviour is denoted by B, and the state or the situation that provokes a particular behaviour is represented by S at specific time t, then B can be expressed in the following equation (3.1):

$$B = \{ S_{t=1} , S_{t=2} , \dots \dots , S_{t=n} \} \tag{3.1}$$

Each situation carries a set of contextual information denoted by C. Therefore, if each state carries *n* number of contextual information at a specific time point, and state S can be given by the following equation (3.2):

$$S_{t=i} = \{C_1, C_2, C_3, \dots \dots , C_n\} \tag{3.2}$$

In short, driver behaviour is represented by series of actions taken in relation to the emergence of intangible states that carry tangible contexts or contextual information at different time points during the driving process.

A large amount of contextual information can lead to the emergence of various driving behaviours, which can be detected using the sensors (Table 2.2) in chapter 2. The table presents the possible values of contextual information; however, it is not an exhaustive list of all the values of contexts regarding a particular state of the driver. Therefore, further possible contexts can be included and analysed with respect to a particular state of driver behaviour.

Based on previous definitions of driving behaviour and the behaviours shown in Table 2.2 in chapter 2, there are three classes of driving behaviour.

3.2.1 Normal behaviour

The behaviour of the driver is considered normal when he or she concentrates on driving tasks, keeps his or her eyes open, keeps the vehicle in its respective lane, avoids sudden changes in acceleration, drives without intoxication and controls the speed and velocity of the vehicle according to well-defined traffic rules. The compliance with the foregoing criteria gives rise to normal driving behaviour.

3.2.2 Reckless behaviour

When drivers drive vehicles on the road with sudden changes in acceleration at high speed beyond the speed limit, they can put the lives of others and the driver at risk. Such behaviour is termed reckless driving behaviour [117], [118].

Nowadays, reckless driving has become a critical subject in communities worldwide, especially with regard to young drivers. Moreover, it is considered a manifestation of driving misbehaviour. It is better to start by defining the reckless driving behaviour from the perspective of the law. Reckless driving behaviour refers to a driving style in which driver ignores the traffic rules and regulations wilfully without caring about the consequences of his or her actions for other road users. Consequently, the drivers' actions in this behaviour are more likely to cause road accidents and damages. This is considered more serious offence compared to the careless or improper driving; and it is normally punishable by heavy fines, imprisonment and annulment or suspension of the driving license depending on severity of the damage caused by the reckless driving [119].

Reckless driving behaviour can also be characterized by criminal tendencies to damage the smooth flow of traffic on the road, "conscious indifference to the safety of others", headless and rash, and furthermore "characterized by the creation of a substantial and unjustifiable risk of harm to others and by a conscious (and sometime deliberate) disregard for or indifference to that risk." The driver's reckless behaviour can be described as a conduct "much more than mere negligence: it is a gross deviation from what a reasonable person would do."[120].

The penalties and punishments given to reckless drivers vary from country to country. For instance, Japan has categorized the reckless driving behaviour into two types: dangerous driving and quasi-dangerous driving. The maximum penalty dispensed to drivers showing such a dangerous behaviour on roads is imprisonment for 20 years and 7 years for negligence of the established traffic rules and regulations. The quasi-dangerous driving does not result into death but may cause fatal injuries or lifetime disabilities to the affected road user. The punishment for such driving behaviour is 15 years of imprisonment for quasi-dangerous drivers [121]. This is just a mere example of showing the evolution of various categories of the reckless driving as defined by the Justice systems of a different countries based on the variety of driving behaviours displayed in different situations.

3.2.3 Aggressive driving behaviour

Aggressive driving behaviour is similar to reckless behaviour in terms of driving the vehicle at dangerous speeds. However, the spectrum of characteristics of aggressive behaviour expands to tailgating, weaving in and out of lanes, being pushy and impatient during driving, ignoring or failing to obey the established the traffic norms, promoting the risk of collision, displaying hostility, annoyance and the deliberate will to save time at the cost of putting others at the risk [117], [118].

Aggression can be defined as any behaviour directed at causing physical or mental injury [122]. In addition, the classification of an act as aggressive depends on the subjective judgements of intention and causality [123].

The first definition of aggression in driving includes what are normally classified as extreme behaviour. These are acts of murder, suicide and wilful and malicious assaults (physical or psychological). The second definition encompasses the concept of risk taking. This type of driving behaviour is aggressive in appearance, but it does not necessarily imply intent to cause harm although it may subsequently put other road users at risk [122], [123]. On the other hand, driving behaviour is considered aggressive if it is deliberate, likely to increase the risk of collision and is motivated by impatience, annoyance, hostility, and/or the attempt to save time [123]. In addition, aggressive drivers operate a motor vehicle in a selfish, pushy or impatient manner that is often unsafe and directly affects other drivers [118].

The National Highway Traffic Safety Administration in the US in (2009) reported a highway safety countermeasure guideline for state highway safety officers: “Is generally understood to mean driving actions that markedly exceed the norms of safe driving behaviour and that directly affect other road users by placing them in unnecessary danger”[124].

3.2.4 The most dangerous driving style, tafheet

Tafheet is a very popular driving behaviour that is characterized by driving non-modified cars at dangerously high speeds (~100-161 miles per hour) on public roads, drifting the cars sideways, breaking traffic rules, barriers and putting the lives of road users at great risk. Tafheet drivers spin the cars at 180 and 360 degrees repeatedly and periodically while driving on highways, in addition to performing a multitude of spins and turns. However, the nature and extent of such manoeuvres may vary from driver to driver [125]. Further discussion of tafheet behaviour will be provided in Chapter 7.

Skilled drivers can manoeuvre through the narrowest and most curvy roads. However, they cannot do so if they use only the throttle for speed control and the steering angle as the only means of turning. Using the throttle in conjunction with the steering angle can cause the back wheels to lose traction while navigating a turn. This results in the rear part of the vehicle moving out of the turn, forcing the vehicle to rotate while the direction of the speed is unchanged. Drifting is achieved when the throttle and steering cause the vehicle to stop rotating relative to the vehicle speed. The angle between the front of the vehicle and the direction of the speed is called the sideslip angle [126, 95]. This driving style is a combination. Drifting is a sport driving technique that entails irresponsible reckless driver behaviour. Unfortunately, most young drivers use vehicles as toys and killing machines.

Tafheet is a dangerous driving style practiced by a great number of Saudi youths. In Saudi society, drifting is known as *tafheet*, *hajwalah*, or *farfarh*. According to [97], drifting was banned by the Saudi authorities because it was responsible for serious road accidents. Tafheet is a threat not only to road users but also to the wellbeing of the society because it increases traffic noise. Tafheet can be done at both low and high speeds. In the latter case, the driver forces the car to spin out at terrifying speeds (180-200 km/ph). Addressing this particular case is possible by using the existing Saher system (camera system). Low-speed tafheet (50-70 km/ph) occurs at roundabouts, crossings and U-turns [95].

A summary of the characteristics of reckless, aggressive and tafheet behaviours is provided in Table 3.1.

Type of behavior	characteristics
reckless	Ignoring the traffic rule, likely to cause accidents/damages, serious offence compared to careless driving; conscious indifference to safety of others, headless, rash
Aggressive	Reckless behavior plus speeding the vehicle, tailgating, weaving in and out of lane, pushy and impatient, more , likely to cause accidents/damages, more serious offence compared to careless driving in terms of fines and punishments; display of hostility and annoyance feelings; motivated to save time
Tafheet	Speeding (100 miles/hr to 160 miles/hr); most likely to cause damage and accidents; more serious offence compared to aggressive; spinning acres at 180 and 360 degrees on road; drifting cars sideways; breaking barriers and traffic rules, motivated by seeking attention of others on road and show off of his driving skills

Table3. 1: Summary of characteristics of different types of driver's behaviour.

3.3 Bayesian Networks Overview

This section presents the static Bayesian networks (BNs) and dynamic Bayesian networks (DBNs), on which the behaviour detection algorithm used in this thesis is based.

3.3.1 Static Bayesian networks

BNs are also referred to the "belief networks associated with the family of probabilistic graphical models (GMs). The graphical structures derived through this modelling yield information about the domains of uncertainties in a specific context. The nodes in the graph represent the random variables, while the edges show the regions of probabilistic dependencies, which are often calculated using various complex computational and statistical methods. The variables presented in the nodes in a graphical structure can be discrete, such as nodes with high or low values, and continuous, such as speed, acceleration and age, which are represented in real number formats, such as 5, 15, 25 etc.[127], [128], [129]. In the current thesis, only the discrete values of the variables are employed. Therefore, BN derives its rigorous modelling approach by combining mathematics, statistics, computer science, probability theory and graph theory [9], [66], [127], [130], [131].

BNs with GMs having undirected edges are called Markov networks or Markov random fields. They are normally applied to derive the independence factor between two distinct nodes located in the Markov blanket. They are used in the modelling of computer vision and statistical physics. However, BNs with GM having a directed acyclic graph (DAG) are considered mathematically rigorous and intuitively simple and explicable. They are commonly applied in artificial intelligence, machine learning and statistics [83], [128],

[132]. BNs are able to obtain information about the static components of the domain, so they consider only observations at a specific time point to perform the inferential process.

The structure of DAG consists of two main domains: directed edges and nodes. The nodes are usually drawn in the form of circles and labelled with names of respective variables. Similarly, the directed edges are represented by arrows and show causal relationships between the two random variables. The actual edges are statistical expressions of the dependence between two variables. For example, in the simple three-node Bayesian network shown in Figure 3.1, the three circles represented by Xi, Xj and Xk are the random variables shown in the DAG structure. The arrow indicates that value assumed by variable Xj and Xk will be affected by the values taken by the parent variable Xi, which means that sates of both variables Xi and Xk are influenced by states of Xi. Thus, node Xi can be denoted by parent variable as root variable as it has no parent, similarly, the variable Xi and Xk are designated are children of Xi, which can also be termed as the leaf nodes as they don't carry their own children. Similarly, the extrapolation of these genealogical terms can define and describe a set of nodes/descendants. As nodes Xj and Xk are only affected by Xi, so they are conditionally dependent on the Xi.

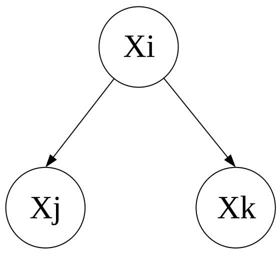

Figure 3.1: Three-node Bayesian Network

BNs have brought about the significant development and achieved a great milestone in modelling both static and dynamic aspects of the situation or state for the characterization of an event. BNs used to characterize the time dependent data are also referred to dynamic Bayesian networks, which are actually created by combining the static BNs sequentially at different time points. The connections between two neighbouring time points can be defined and modelled by applying the first-order Markov model, which shows that an event at a particular time point ‘t’ will be affected by the random variables at that point and those at time point (t-1)[89], [91], [92]. Hidden Markov Model is another version of DBN in which hidden state of an event can be represented by considering only a single random variable, whereas in DBN hidden state of an event is characterized by a set of random variables. Moreover, the graphical topological of HMM is restricted compared to that of DBN [87].

3.3.1.1 Conditional probability table (CPT)

Each random variable in the BNs is associated with CPT, which gives the probability distribution of nodes and the strength of a causal relationship between the given two nodes in the DAG structure. The size of the CPT may vary depending on the number of parent nodes, child nodes, and the states of nodes in the BNs. Probability distribution gives the probability of node being in one state out of its several potential states. For Boolean networks, the node having z parents has the 2 z+1 probability in conditional probability table. Hence, the reduction of parents leads to the overall decrease in size of CPT [127], [128], [129].

In order to obtain the values of probabilities in CPT for each node in BN, the following two approaches are employed [11], [78], [133]:

1. First training data is obtained by employing several tests in the system designated as a test system followed by collection of output data from various tests performed to solve various cases for the same issue under investigation. Statistical analysis can then be performed to achieve a set of values that undergo a rigorous learning algorithm to learn or parameterise the CPT from this data. Different learning algorithms are available in the market in the form of software packages like Expectation Maximisation (EM) [127].
2. CPT can be obtained by parameterising the network by utilizing the data obtained from the previous studies or published research work about the similar or related to research issue under investigation.

Some researchers did not employ the test bed equipped with sensors because of difficulties in acquiring data, but in the current study, the author performed the experiment successfully with a test bed equipped with sensors. The data obtained will be elaborated extensively in Chapters 5 and 6. Hence, the current study adopted the first approach to procure the CPT values for the network.

3.3.1.2 Reasoning with Bayesian networks

Reasoning is performed with BN by calculating the values of probability distributions for the posterior node or a set of nodes, which can be mediated by circulating a new set of information all over the networks without taking the directions of edges into account. This method is referred to inference or probability propagation [127], [134].

There are four main categories of reasoning process in BNs Figure 3.2

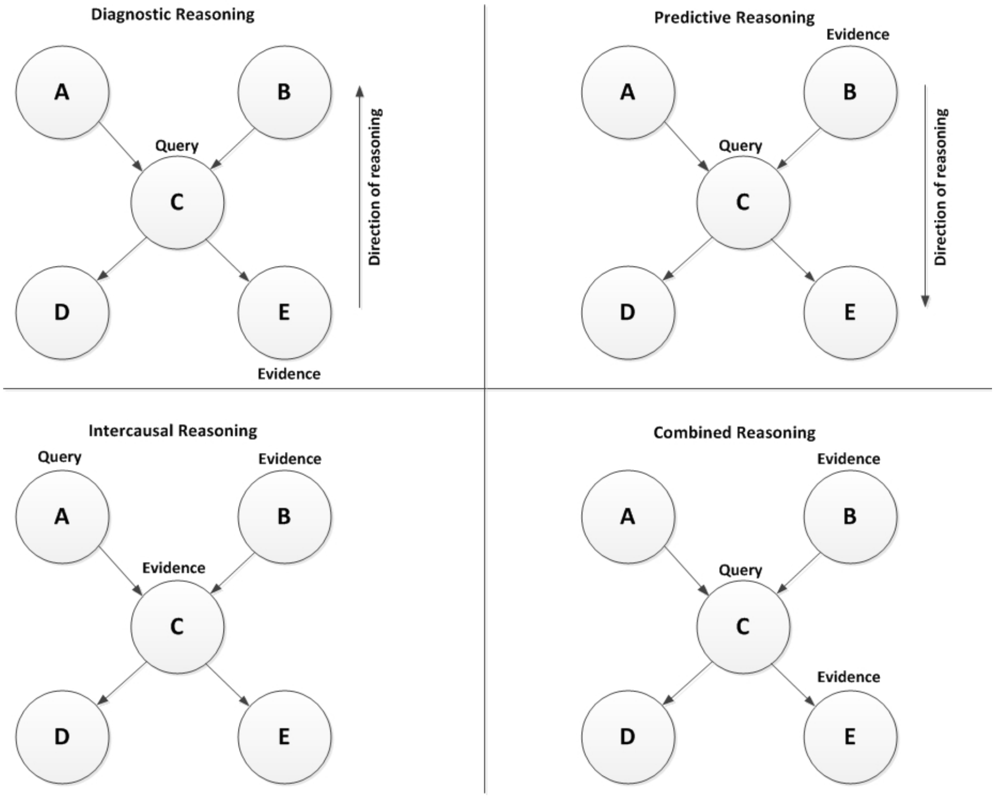

Figure 3. 2: Reasoning with Bayesian Networks [127]

- Diagnostic reasoning

This category of reasoning is applied in the opposite direction of edge in order to have a belief about the specific state of a particular node. For example, in order to have the belief that node C is in the correct specific state, information and evidence are gathered about the states of the B or A in figure 3.2 (a).

- Predictive reasoning:

This type of reasoning is in the direction of edge or an arrow interlacing the two nodes. This means that knowledge and evidence collected about the state of node B will increase the strength of belief in the particular state of node C in figure 3.2 (b).

- Intercausal reasoning

This method of reasoning considers mutual causes for the common effect observed in the BNs. The common causes are independent such that obtaining new evidence about node A will not change the belief in the state of B; however, finding the new evidence about node C will strengthen the belief about nodes A and B. Interestingly, finding new information about B is likely to increase the belief in the state of node C and simultaneously decrease the belief in the state of node A. This has been explained in figure 3.2 (c).

- Combined reasoning

In certain cases, the application of either diagnostic reasoning or predictive reasoning does not give satisfactory results; therefore, both reasoning methods are applied in combination to explain a particular scenario. In the current thesis, the combined reasoning method will be used, which deals with both concepts of cause and effect in BNs.

Bayesian networks can be observed in two formats: a singly connected network in which any pair of nodes has only a single relationship with either side of the node in the network; and multiple connected networks in which any pair of nodes in the network may have more than one path or relationship [89], [135].

Similarly, there are two categories of inference algorithms in BNs: approximate and exact inference algorithms. The example of approximate algorithm can include model simplification methods, loopy belief propagation, search based methods and stochastic simulation algorithms, similarly, polytree, clustering, symbolic probabilistic inference, variable elimination, arc reversal are some examples of exact inference algorithms. Both these inferential methods involve the extensive computations and analytical expertise on the behalf of the user. However, the speed of inference depends on the size of the network, position of hypothesis nodes, and number of undirected loops. When the BNs size continues to grow in size, the use of approximate inference algorithm is preferred compared to the exact inference algorithm.

There is no single inferential algorithm for any problem. Therefore, all problems require the combination of suitable inference algorithms to be applied in order to execute the inferential process of BNs. The researcher must understand the nature of the problem, possible domains of the problems, and then move onto the in-depth understanding of domains of inference algorithms before considering the suitability of inference algorithms for the solution of a specific problem[127], [128].

In the current study, the nodes are singly connected forming singly connected BNs. The hypothetical nodes carry both parents and children, and the size of the BNs is moderately large. Therefore, the polytree inference algorithm was selected to execute the inference because it works efficiently in moderately large networks and performs an efficient exact inference algorithm in the current singly connected BNs.

3.3.2 Dynamic Bayesian networks

The dynamic Bayesian network (DBN) model describes a system that undergoes change dynamically or evolves over time. This model is important in describing systems in which the user can monitor the set of changes or observations detected with the passage of time. It allows the user to predict the future behaviour of the system. The word “dynamic” in

DBN does not mean that system undergoes changes automatically; rather it refers to the "motive force". Because static BNs cannot model the motive forces that are static to single time points during the event, the dynamic BNs are adopted to evolve the dynamic model. Every system in real life changes its states over time. It is appropriate to differentiate between the terms temporal and dynamic. The temporal model refers to a modelling event in which time is taken as a continuous permanent entity without considering the innate changes in the system during the continuum of the time. Therefore, temporal models represent a sub-category of dynamic models. Suppose that each time point in the temporal model is taken as equivalent to a specific change of the system. If the movement of these time points reflects the changes in the system's states rather than time, the model is categorized as a dynamic model.

However, when the change in time is considered with respect to temporal models, two approaches adopted to explain the time change: time-point representation and time-interval representation. The latter expresses the time points in a consecutive order, which may cause confusion in the detection of state at a single time point. Therefore, the former seems more suitable and meaningful in terms of expressing change in a state at a particular time slice. DBNs are considered special cases of singly connected BNs, which are connected mainly through interlaced time-points in sequential order. Each time-point reflects the evolving event at a particular time slice/point [11], [86], [89], [92], [135], [136]. All nodes, edges and probabilities in DBNs are identical to those in BNs. Random variables in DBNs represent specific states because they indicate the temporal dimension. The state in DBNs fulfils the criteria of the first order Markov property, which can be defined as the state of any system at the given time point "t" within DBNs, depending on its immediate past "t-1". Future DBNs states can be predicted by considering only the present state without reliance on the immediate past.

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i\,|Pa(Z_t^i)) \qquad (3.3)$$

With the expansion of BNs, connections appear between the time-points that are called the intra-time-points connections. They also appear between the time-points in various time-slices called inter-slice connections. These temporal connections set the condition probabilities between variables belonging to various time points, thus giving rise to the time-dependencies arranged in the transition matrix, which is called a conditional probabilities table because they are presented in a tabular format. Similarly, the conditional probability distributions of intra-time point connections are represented in tabular form. Therefore, they are called CPT.

$$P(Z_t|Z_{t-1}, Z_{t-2}, \dots, Z_{t-k}) = \prod_{i=1}^{N} P(Z_t^i\,|Pa(Z_t^i)) \qquad (3.4)$$

The states of DBNs are not directly observable, unique or simple, but they may be influenced by other variables that are measured or calculated. Each state at a given time slice in DBN relies on a single state or multiple states in previous time slices and/or on those in current time slices. Thus, each state of the DBN is characterized by a complex structure. Therefore, each state in DBN at the given time slice "t" possible depends on the nodes at the same time instance and/or on the states of the system at time "t-1"

3.3.2.1 Inference

Two methods are normally suggested to perform the exact inference process for the DBN. The first approach considers the DBN as equivalent to the static BNs after unrolling the DBNs, so any inference methods suitable for static BNs can also be applicable to DBNs. The second approach takes the path of converting DBN into hidden Markov Model (HMM), followed by application of forward-backward algorithm[92], [129], [135]. In this study, the former approach is used by assuming that both DBN and static BNs are identical after performing unrolling the DBNs, followed by the application of polytree algorithm in order to perform the inference process.

3.3.2.2 Designing dynamic Bayesian network

The following four steps are taken in order to design the DBN:

- Providing definitions of hypothesis nodes/variables, which are the nodes to be inferred. These information nodes affect the hypothetical nodes. The observable nodes/variables arise from the hypothetical nodes/variables
- Sketching the causal connections between the variables/nodes in network
- Giving the specifications of CPTs for each node in the network
- Executing the inference process on the hypothetical nodes

3.3.3 Dynamic Bayesian networks software

The common tools used for the DBNs are given below [127], [129]:

- The Bayes Net Toolbox (BNT) for Matlab
- Netica

- Analytica
- The graphical model toolkit
- BayesiaLab
- Probabilistic Network Library (PNL)
- GeNIe

However, GeNIe was used for this study due to several advtanges compared to other tools. The details of GeNIe and its merits has been presented in the following section.

3.3.3.1 GeNIe

This is a very efficient and timesaving software with several graphical user interfaces and provides options of many inference algorithms, in contrast to the previously described software, for both approximate and exact inferences, such as likelihood sampling, clustering, logic sampling, polytree and so on [142]. It is also able to support discrete variables/nodes and offer the user the option of DBN files and import and export functions, which makes it a highly user-friendly package. It also allows the user to pinpoint the nodes of interest in DBNs, which undergo regular inference processing, and it is updated continuously, which saves computational activity by the user. This program is implemented in C++ language, and is a graphical interface of SMILE, which is a collection of functions for probabilistic and decision making network models. This special software allows the user to construct a diverse range of simple and complex, medium sized and large-sized BN and DBN networks through the use of temporal reasoning functionality [127], [129].

Although several open-source and commercial programs are available for the implementation of DBN, each has advantages and disadvantages. Moreover, there are no criteria for using specific tools for DBNs. Therefore, based on the advantages of GeNIe and its suitability, the GeNIe version 2.0 software was chosen for the current study,.

The reasons that this software is suitable for the current study as are follows:

- Free availability
- Graphical and user friendly interfaces
- Implemented in Windows operating systems
- Supports the import and export of DBN files; moreover, it allows the copy and paste function in the Genie spreadsheet
- Ease of construction of DBN networks and of defining the nodes of interest
- Option of applying polytree inference algorithm chosen for the current study
- Offers graphical illustrations as bar charts and gives the probabilities associated with each state of the DBN
- Provides the option of temporal reasoning for the implementation of both BN and DBN in order to construct first-order Markov DBN

3.4 Summary

This chapter overview of the prevention of accidents by employing VANET in the context aware manner has been presented. The normal and abnormal behaviours of the driver have been presented in the perspective of context aware system. In this thesis, three kinds of abnormal behaviours were considered for the detection by the proposed model:

Tafheet, reckless, aggressive and normal behaviour. The requirements and conditions for the detection of these behaviours were also elaborated. Various functionalities and features of BN including the different phases such as sensing, implementation, reasoning and decision making by the use of inference algorithms were explained, along with the selection of Polytree algorithm for performing the inference. The comparison was made between the chosen algorithm and other available algorithms used for this purpose.

Moreover, the DBN model and its features were described with the focus on its ability to deal with uncertain data accurately and to conduct a probabilistic inference on the dynamic data obtained through driver's behaviour. The explanation and justification of the mathematical concepts and inference methods applied on various time slices of the driving action were presented in this chapter.

The overview and features of the main software packages used to implement the DBN model was given along with their merits and demerits. The selection and justification of the application of GeNIe 2.0 software was explained for the implementation of the proposed DBN model of this study.

The subsequent chapter will show the elaborated OBU driver behaviour detection architecture.

Chapter 4

On Board Unit Architecture Based on Context-Aware system

This chapter presents the following:

- **A novel on-board unit architecture (OBU) architecture for the driver behaviour detection system in VANET**
- **Main phases/layers of the proposed architecture based on context-aware system concept**
- **Definition and description of the various components of the proposed OBU architecture**
- **Explanation of the mechanism of the driving behaviour detection system**

4.1 Introduction

In this chapter, a detailed presentation of components of the proposed OBU architecture in VANET is provided to gain insight into its working mechanism. In addition, the mechanism for the detection of abnormal behaviours of drivers is described fully. The novel architecture with various components is presented. The architecture is built with the integration of the sensing phase, the processing and thinking phase and the action phase. The composition and structure of the sensors are described in addition to the working principles of the sensory devices. A flow chart elaborates the working principle of the proposed OBU architecture.

The functions of all of three phases of the proposed architecture: the sensing phase, the processing and thinking phase and the action phase are fully explained to give a complete understanding of the working principles of the OBU architecture. The algorithms used for the behaviour detection and the corrective action are explained, and their roles in the processing activity of the OBU system are emphasised.

4.2 Mechanism used by the Architecture to Detect Driver Behaviour

In this section, the detailed mechanism of how the proposed system seeks to detect the driver is presented and illustrated in Figure 4.1. The information about the context of the environment, the vehicle and the driver is collected by the virtual and physical sensors connected to the OBU, such as GPS, ECG sensor, gyroscope sensor, thin-film force sensor and so on. The information collected by the sensors is interpreted by micro-controllers into forms suitable for processing by the processor fitted in the OBU. The detailed description of the micro-controller will be given in Chapter 5. The ontology modelling technique is a powerful technique employed for the conversion of sensory data into the machine-readable form [63].

The sequence of events performed by the system to detect drivers' behaviour is as follows: capturing contextual information; conversion of sensory data into a machine-processable form for the OBU processor; and knowledge of driver's uncertain behaviour by applying the behaviour detection algorithm (DBN) and the probabilistic inference method. If the output data show the normal behaviour of the driver, all criteria of normal behaviour will be shown to be satisfied. This will not require any further action on behalf of the processor. However, if any abnormal or tafheet tendencies are detected in the driver's behaviour, the processor will process the information and trigger the corrective action required to be taken by the surrounding vehicles. This is facilitated by utilizing the algorithm related to the velocity, position and direction of surrounding vehicles. The corrective actions will be sent in the form of signals by the processor to the DSRC/WAVE control unit, which will process the information and pass it on to the wireless transmission unit. The wireless transmission unit is responsible for broadcasting the HELLO beacon message.

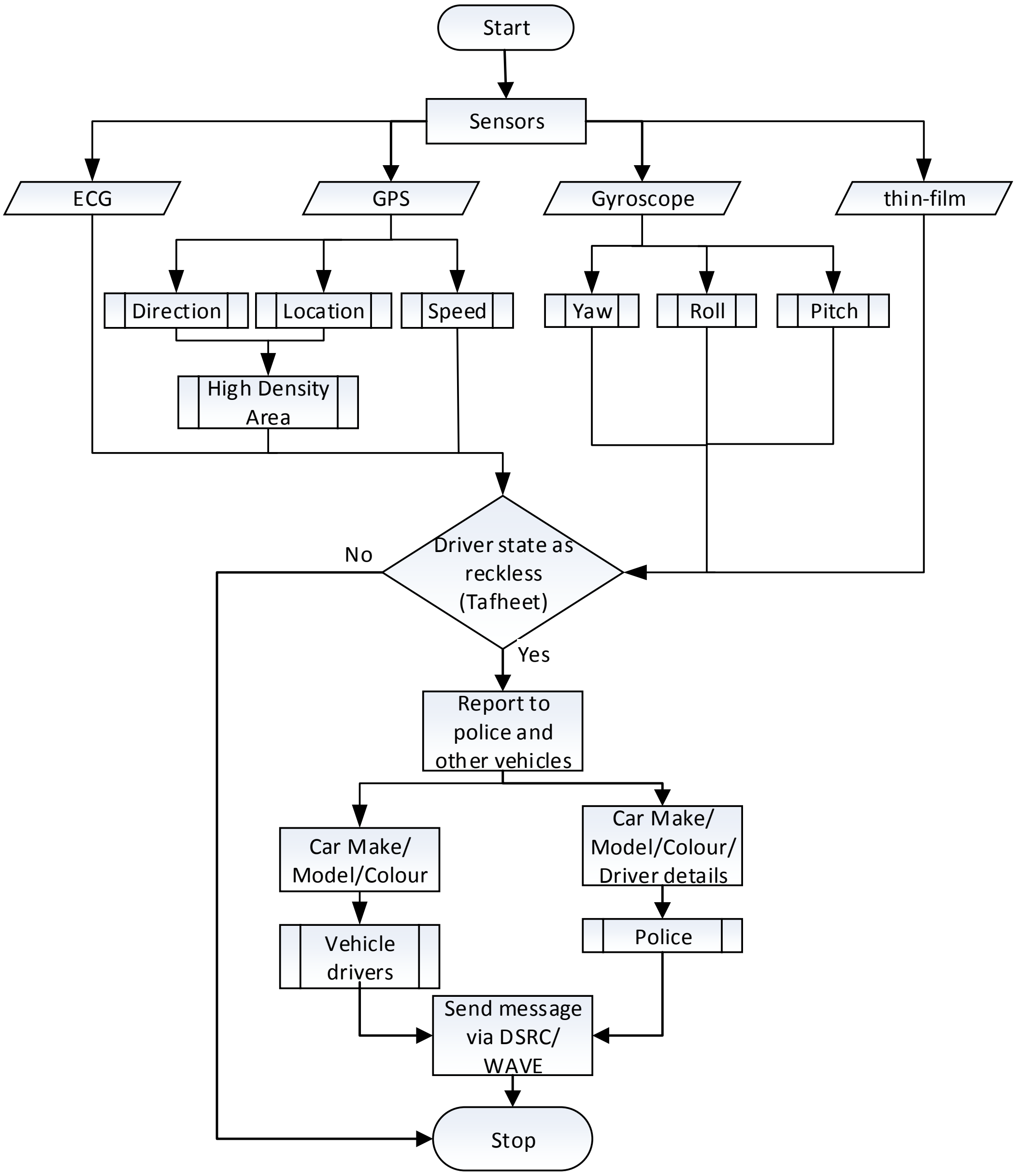

Figure 4.1: Mechanism of the driving behaviour detection system

Following the calculation of the surrounding vehicles on road, warning signals are issued by the wireless transmission unit on receiving the input data from the processor through DSRC/WAVE control unit. The calculation and corrective action algorithm will be presented in Chapter 6. The functions of the proposed system work—sensing the contextual information, performing reasoning and inferring the corrective actions based on the input data—are based on the principle of the context aware system and are carried out instantly.

4.3 OBU Architecture

The OBU architecture in VANET, which is designed for the detection of driver's abnormal behaviour (tafheet), includes various components. The illustration of these components is shown in Figure 4.2.

The figure reveals the layout of all of system's components, and shows how they cooperate with each other to accomplish the task of determining anomalies in the driver's behaviour and issuing warning messages to the driver by utilizing the in-vehicular alarms.

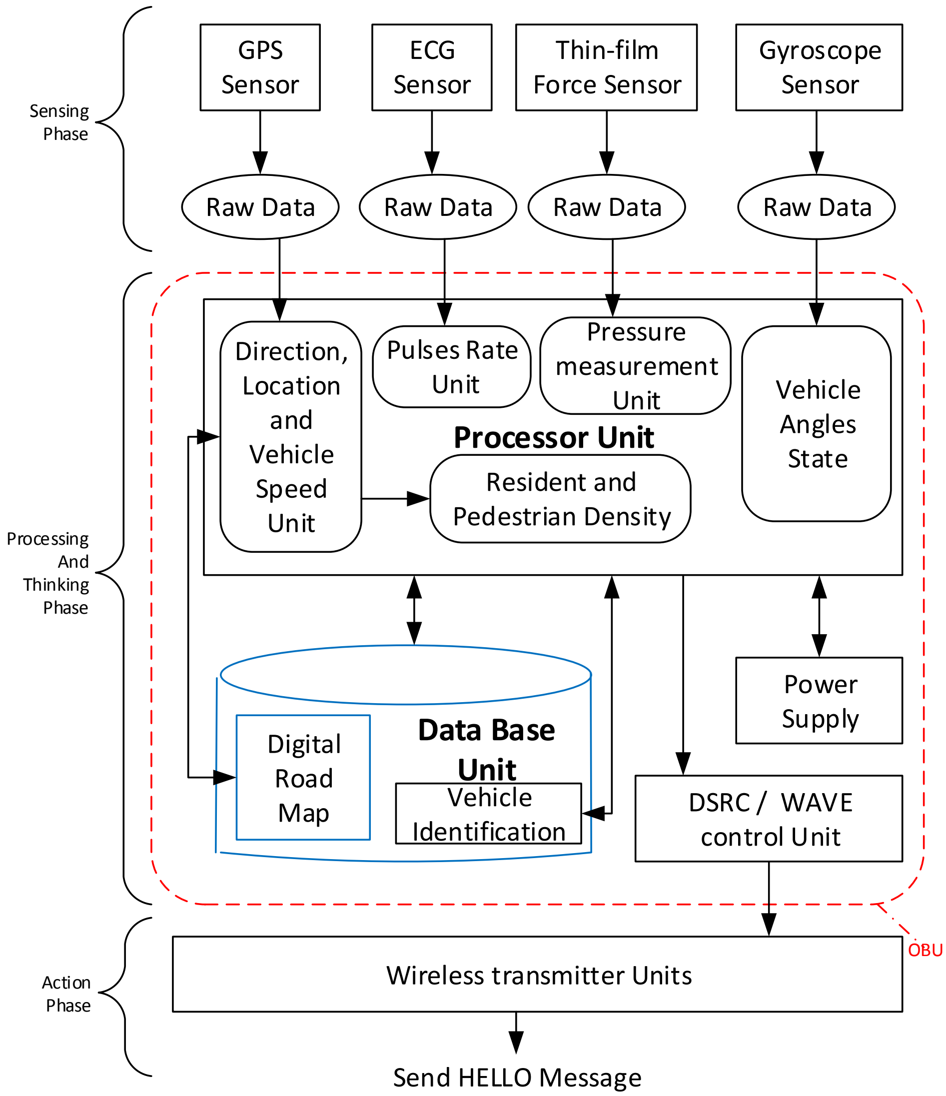

Figure 4.2: On-board unit context-aware architecture for detecting tafheet

The architecture consists of three main phases: sensing, Processing and thinking phase and action. The context aware system of architecture contains three major context-aware sub-systems: sensing, reasoning and acting. Figure 4.2 also shows the interdependence of the phases in performing certain actions. For example, the alarms are operated in the third phase, which collects input data from the second phase, which in turn depends on the first phase for the delivery of input data to complete the task.

In the three-phase contextual frameworks, in the sensing phase, the sensors are located in the sensing layer and the raw data retrieval layer. The processing and thinking phase consists of the processor with all the sub-units, the database, the power supply and the DSRC/WAVE control unit. The action phase contains the wireless transmitter unit, which sends the HELLO beacon message.

4.3.1 Sensing phase

The section will provide the details about the mechanism of the data collection and the types of sensors involved in this process. The sensing phase is part of the sensing sub-system in the context aware system. This phase performs the task of collecting data on the driver, the vehicle and the environment. It then transforms the collected data into machine-processable data that are ready for the reasoning phase. The sensing phase is divided into two layers: the sensory layer and the raw data retrieval layer.

4.3.1.1 Sensory layer

This layer consists of variegated sensors that are specialized for the collection of data from different contexts. It is directly connected to OBU of the vehicle, which is the main operating hub of the proposed architecture. As described in Chapter 2, three kinds of sensors—physical, virtual and logical sensors—gather data related to the environment, the vehicle and the driver. In the proposed architecture, the sensing phase consists of physical sensors that constitute the internal data sources equipped within the vehicle, such as the speed and GPS sensors, the ECG sensor, the gyroscope sensor and the thin-film force sensor. They provide information about vehicle angle states, pressure of the driver's grip on the steering wheel, heart beat rate, location and direction to identify areas with high population density and speed.

The data collected from the physical sensors are transmitted to the processing and thinking phase. The functional success of the architecture depends on each component of sensory phase. The failure of a single sensor in the system will lead to the retrieval of inaccurate data, which can compromise the system's performance.

The details of each sensor used in the architecture are described below:

- GPS: Global position system (GPS) helps to collects the data regarding the speed of vehicle, current time, speed limit on the road, and offers assistance to drivers to keep their speed, position and direction of the vehicle [14], [143].
- ECG sensor: These are special sensors designed to gather information about the rate of the change of heart pulse, and can provide information about the normal or abnormal state (Tafheet) behaviour on the specific point on the road [144], [145].

Abnormal driving, such as aggressive, reckless and tafheet, involves high speed. In high-speed driving, physiological conditions undergo high sensory stress, which results in an increased heart rate (number of beats per minute) [146]. Because tafheet behaviour is a dangerously high-speed driving phenomenon, the ECG sensor was used to record the changes in heart beat rate as an indicator of changes in speed. This increased accuracy and efficiency of the tafheet behaviour detection system was combined with other sensors used in this study. For example, changes in heart rate recorded during various intensities of exercise by different age groups are shown in Figure 4.3. Similar changes in heart beat patterns are expected to happen during rash and high speed driving, which further justifies the use of the ECG sensor to detect tafheet driving behaviour accurately. The heart rate of the heathy person [147]

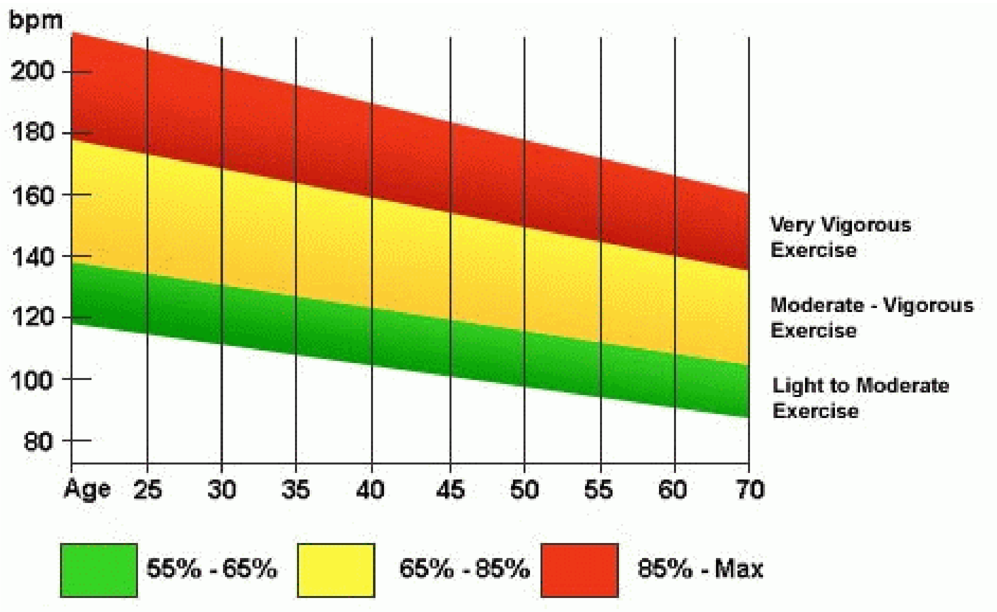

Figure 4.3: Target heart rate zone [147]

- Thin-film sensor: These special sensors capture the different states of the driver's grip on the steering wheel to provide information about aggressiveness and recklessness or the combination of both reckless/aggressive, which defines tafheet behaviour [148].

The thin-film sensors provide the handgrip measuring system with high resolution. The device can be directly worn by the user on the hand or it can be worn in the form of gloves with built-in thin-film sensors. In both forms, the handgrip force measuring system performs equally well. Each sensor carries the 18 sensing regions, which can be placed around the anatomic section of palm and the fingers. The free spaces between the sensing regions allow the joints to be free of the device structures. The pressure of hands on various points on the object is identified by the use of multiple sensing elements (sensels) located within the grip system [149]. Data about the pressures/forces applied by various regions of hands on the object are recorded and saved by the device. For males and females, the device is capable of measuring the handgrip force in the ranges of 30.4 kg–70.4 kg and 14.0-38.6 kg, respectively [150].

Variations in the handgrip force according to age are shown in Table 4.1. Males between 20 and 50 years showed constant strength. In the female group, the maximal strength was recorded between the age of 30 and 40 years. The grip was found to be weaker when the extremity was supported [149].

Age	Grip , Kg			
	Male hand		Female hand	
	Major	Minor	Major	Minor
20	45.2	42.6	23.8	22.8
20 -30	48.5	46.2	24.6	22.7
30 – 40	49.2	44.5	30.8	28.0
40 – 50	49.0	47.3	23.4	21.5
50- 60	45.9	43.5	22.3	18.2

Table 4. 1: Average strength of grip based on age [149]

- Gyroscope sensor: This sensor gathers information about serious changes in driving behaviour according to three angles (x, y, and z). The gyroscope is supported by three kinds of sensors, roll, pitch, yaw, which are able to measure changes in three dimensions. The gyroscope sensors detect any serious changes in all three dimensions of the vehicle. The raw data are sent to the vehicle angle state for further processing.

The sensors and their functions are as follows:

(i) *Yaw sensor*: It collects information about the dimension of vehicle along the z-axis. The turning of the z-axis is recognised as the heading of a vehicle. The z-axis is aimed down and out of the vehicle. To coil around it would cause a change of the travel direction in the navigation frame. As shown in Figure 4.4 and Eq. (4.1), the yaw is calculated using the formula provided [151]:

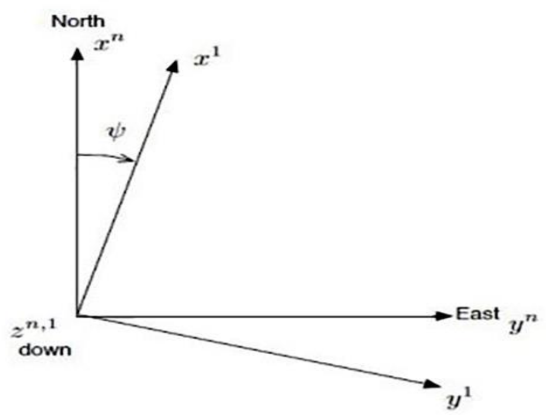

Figure 4.4: Yaw turning following right-hand rule [151]

$$\mathbf{R}(\psi) = \begin{bmatrix} \cos(\psi) & \sin(\psi) & 0 \\ -\sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} = \mathbf{C}_1^n \tag{4.1}$$

(ii) *Pitch sensor:* The turning of the y-axis indicates the pitch angle in avionics because the y-axis essentially aims down the balance level of the vehicle. As shown in Figure 4.5 and Eq. (4.2) the pitch is calculated as follows [151]:

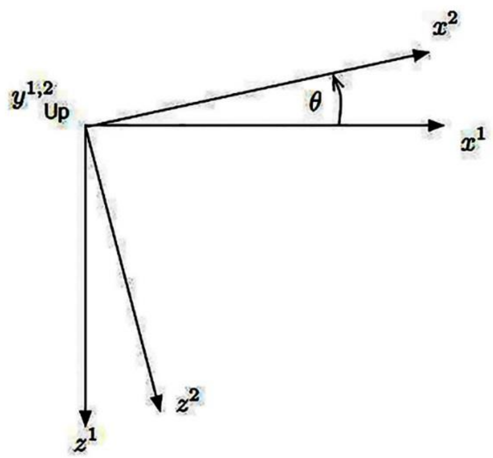

Figure 4.5: Pitch turning following right-hand rule [151]

$$\mathbf{R}(\theta) = \begin{bmatrix} \cos(\theta) & 0 & -\sin(\theta) \\ 0 & 1 & 0 \\ \sin(\theta) & 0 & \cos(\theta) \end{bmatrix} = \mathbf{C}_2^1 \tag{4.2}$$

(iii) *Roll sensor:* The turning of the x-axis is recognised as the roll, which indicates avionics. The x-axis departs from the central mass of the vehicle, leaves the front and follows the same direction as the vehicle itself. As demonstrated in Figure 4.6 and Eq. (4.3), the roll is calculated as follows [151]:

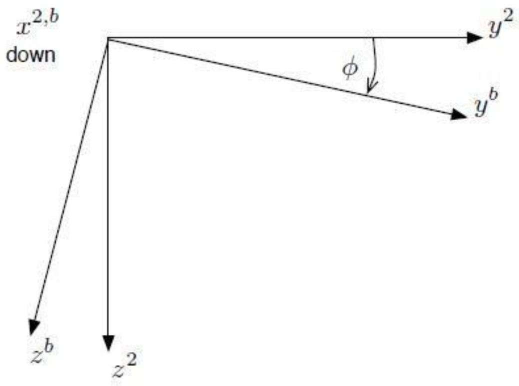

Figure 4.6: Roll turning following right-hand rule [151]

$$\mathrm{R}(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & \sin(\phi) \\ 0 & -\sin(\phi) & \cos(\phi) \end{bmatrix} = \mathrm{C}_b^2 \tag{4.3}$$

4.3.1.2 Raw data retrieval layer

This layer receives input data from the sensory layer and performs two important functions: the separation of low-level sensing details from the sensors to make it suitable for the system's upper layer; and the processing of contextual data received from the sensory phase. This layer comprises two important parts, which are detailed below:

- Data Acquisition Part: This unit performs the tasks of controlling the sensors and balancing the coordination level among various sensors in order to gather information consistently.

- Context Interpreter Part: This component is responsible for converting the sensory data received from the previous phase into machine-executable form by applying a modelling technique, such as the ontology modelling method. The processed data are then transmitted to the processing and thinking phase for the deduction of inferences (the modelling technique applied by reasoning is beyond the scope of this work). The abstract form of the data may be received from various kinds of sensors, such as GPS, ECG and gyroscope sensors.

4.3.2 Processing and thinking phase

This phase constitutes the reasoning sub-system of the architecture in which information received from the previous sensing phase is processed and reasoned by utilizing the appropriate tool. Drivers' behaviour is referred to as high-level contextual information or uncertain contextual information, which is gathered by applying different sensors that are present in the sensory phase. Reasoning about the information related to the driver's behaviour is performed by using the the DBN-based behaviour detection algorithm to differentiate between normal and abnormal behaviour and tafheet. When the reasoning is performed and the driver's behaviour is detected as abnormal or tafheet, the corrective action algorithm is applied to convey the corrective action to the other vehicles on the road in order to avoid fatalities. It is also sent to the nearest police station in order to report the incident.

The processing and thinking phase can be further sub-divided into four units, which are explained as below:

4.3.2.1 Processor unit

This unit constitutes the core unit (processor) of the proposed architecture. It processes and analyses the processed sensory information, it interprets the uncertain contextual data in order to classify the driver’s behaviour as an abnormal or normal. It contains the following various sub-units:

- **Direction and location control unit (DLCU):** The tasks performed by this unit in the proposed architecture is to collect the information related to the direction and location of vehicles with the aid of GPS system connected to it, and to control the dissemination of the received information to the subsequent parts of the architecture.
- **Vehicle speed (VS):** This unit aims to gather all data on vehicle speed. It is connected to the GPS sensors, and it transfers the raw data to the PU unit for processing.
- **Vehicle angle state (VAS):** The VAS unit is connected to the gyroscope sensors. It is responsible for the collection of all data and information related to the vehicle angles in order to identify states and dimensions according to the programmed information fed into it.
- **Resident civilian and pedestrian density (RCPD):** This unit identifies the density area by utilising information from the digital road map, storing it in the database and the storage unit. The GPS unit provides the current location of the vehicle.

- **Pulse rate unit (PRU):** This unit records the driver's pulse, which is analysed by the ECG sensor.
- **Pressure measurement unit (PMU):** to provide the system with driver recorders of the grip force pressure for the steering wheel to be analysed from the thin-film sensor.

The function of the processor is to receive the data from the sensory phase and perform the processing activity by utilizing the following two algorithms:

- Algorithm for behaviour detection: This algorithm is important because it is used to conducting reasoning on the data collected about the driver's behaviour. DBN combines the data collected in the sensory phase with various bits of information about the states of the driver during real-time driving. The driver's behaviour is then categorised as normal or abnormal. For normal behaviour, no action is required, so subsequent phases of the system remain inactive. However, in the case of abnormal behaviour (i.e. reckless, aggressive and tafheet) the processor transmits the signals to DSRC / WAVE control unit, which the corrective action algorithm is performed. The focus of the current thesis is the detection of driver's behaviour, which will be presented in detail in Chapter 6.
- Algorithm for corrective action: This algorithm is used to determine the pro-active corrective based on the position, velocity and direction of other vehicles on the road. The data on other vehicles is extracted from the HELLO beacon messages and pre-loaded digital road maps, which are made available to the processor to

calculate the corrective action. Following the calculation of the corrective action, appropriate signals are sent to DSRC / WAVE control unit, which subsequently transmits warning messages to the other vehicles on the road through using the wireless technology in VANET. The corrective action algorithm falls within the scope of this work.

4.3.2.2 Database unit

This unit is the storage system for the database in the architecture. It has the advantage of being linked to the preloaded digital road map and the GPS system for the verification of direction and location of the vehicle, thereby helping to track the route of the trip in its entirety. In addition, the vehicle identification unit is directly installed in the database unit and is responsible for the provision of all information concerning both the vehicle and the driver to the police and other drivers on the road.

4.3.2.3 DSRC/WAVE control unit

This unit is responsible for transmitting the corrective messages initiated by the processor to the wireless transmitter unit device, which in turn sends them to the other vehicles on the road or to the police through the roadside units in order to prevent road accidents. This device is based on IEEE 802.11p [143] and is situated in the OBU. It uses the wireless radio frequency to connect the vehicle to roadside units or other vehicles on the road. It is able to receive or transmit the signals through the network devices.

4.3.2.4 Power supply unit

This part of the system provides a constant power supply to the OBU and its components, allowing them to perform their functions. This unit is rechargeable.

4.3.3 Action phase

In the proposed architecture, this is the third and final phase of the context aware system. It contains the wireless transmitter units, and it represents the acting subsystem phase. The processed sensory data is passed to the processing and thinking phase, which performs the reasoning task to determine uncertain behaviour such as tafheet. Based on the results of the reasoning process, a set of actions is suggested to correct the abnormal behaviour. The decisions are transmitted through the adaptive broadcasts of the HELLO beacon message to other drivers on the road as a warning notification that contains the car's make, model and colour. A similar incident notification with additional details about the driver and the location is sent to the police through vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I).

4.4 Summary

The chapter presented a context-aware architecture that detects the tafheet driving behaviour exhibited often by young drivers in Middle Eastern countries. By using a wide range of sensors in the sensing phase and a powerful DBN-based reasoning strategy in the reasoning phase and the application phase, the architecture has the capacity to detect tafheet, a highly reckless and aggressive form of behaviour by drivers. With its unique features of reasoning and the instant delivery of decisions by using the HELLO beacon message strategy, the proposed architecture shows great promise in the ability to report incidents of abnormal driver behaviour with greater precision and accuracy than the previously designed systems showed.

In Chapter 5, the tafheet behaviour of drivers will be modelled by using DBN, taking into account environmental and legal factors that are helpful in distinguishing normal behaviour from tafheet driving behaviour.

Chapter 5:

Preparation for experimentation

This chapter presents the following:

- **Collaborations with the researcher and Saudi Arabian organisations**
- **The organisation of the experiments and the recruitment of the volunteers (participants)**
- **The safety precautions taken by the researcher during the experiments**
- **Procedures used in the installation of the device hardware and the selection of a suitable vehicle**

5.1 Introduction

Reckless and aggressive driving occurs worldwide. Tafheet behavior is a combination of reckless and aggressive behaviors. As explained previously it is well known in Middle Eastern countries, Japan and the US. Saudi Arabia is a Middle Eastern country. Several studies and government reports [152], [153] have warned about the effects of this behavior, especially in young drivers.

5.2 Overview of Saudi Organizations Offering Support for the Experiments

The researcher sought cooperation from various Saudi organizations that play an active role in the research and traffic management in the KSA. The names of these organizations are listed below:

- **The King Abdul Aziz City for Science and Technology (KACST)**
- **General Department of Traffic for the Police (GDT)**

The support provided by these organizations was in the form of moral, logistic and consultations, which made it possible to complete the experiments successfully. Without this support, it would not have been possible to complete this project. The subsequent paragraphs provide an overview of these organizations and the cooperation they extended to the researcher. It is important to acknowledge their support because it is the ethical duty of the researcher. Hence, the researcher complied with the ethical considerations recommended by the ethical committee of De Montfort University.

5.2.1 KACST and GDT

King Abdulaziz City for Science and Technology (KACST) is primarily a research and scientific society that was founded and headed by the Prime Minister of Saudi Arabia. It constitutes the major part of the main national research laboratories and research facilities that operate under the directive of the Prime Minister.

In addition, KACST works to establish collaborations between the national and international research institutions to foster innovative and high-quality research.

The researcher collaborated with the KACST due to its critical role for provision of necessary facilities and logistic support to perform the test experiments for determination of tafheet behaviour. KACST was briefed about the research initiative, its usefulness to the KSA, and the requirements for the successful implementation of the current research project. After carefully considering the research proposal, the authorities, showed their willingness to collaborate with the Software Technology Research Laboratories (STRL) in the Faculty of Technology at De Montfort University. Thus, the researcher initiated the collaboration between the De Montfort University and KACST, which will be useful in the future as well in supporting other collaborative research projects. KCAST supported the researcher by facilitating the recruitment of volunteers. The collaboration between the researcher and the traffic police authorities was controlled by the General Department of Traffic (GDT). The researcher contacted the GDT through KACST to request its collaboration in this project. After the collaboration was successfully established, the GDT provided support and assistance to the researcher in his experiments by the means discussed in the subsequent sections.

5.2.2. Contribution of KACST and GDT to the research

The following contributions has been made by KACST and GDT to help conduct the training and test experiments to detect the driver's tafheet behaviour and other behaviours such as reckless and aggressive behaviours.

5.2.2.1 Provision of road space for experiments

The DGT briefed the researcher about safety precautions, the use of the road for the experiments and the allocation of road space for the experiments [155]. The researcher complied with all the instructions and safety precautions recommended by the GDT authorities to undertake the controlled experiments. The GDT does not allow speeds greater than 60 miles/hour. However, in order to record tafheet behaviour, the experiments required the volunteers to perform driving experiments at more than 100 miles per hour. Therefore, the observations about the speed of the users were not recorded because of the safety constraints imposed by the GDT.

The police officers cooperated fully in allocating the road for the experiments by blocking both sides of the road to incoming and outgoing traffic prior to the beginning of the experiments. Hence, because of the coordination and cooperation of the GDT and the KACST, the researcher was able to collect the data from the planned experiments under controlled, real-time driving situations.

5.2.2.2 Assistance in the recruitment of participants

The experiment required the participation of two groups of volunteer drivers. The first group contained sub-groups of different categories of age, gender and others. The second group of drivers contained volunteers with ex-criminal records in the GTD. All the drivers in this group were provided by the GTD and all had previously demonstrated tafheet behaviour [156].

5.3 Installing the Hardware Device

This section presents all the steps used to build the hardware devices, beginning with the selection of sensors suitable for the system architecture. All necessary parts were put together in order to obtain the raw data to be analysed by the proposed system. Figure 5.1 shows the working arrangement of the sensors in the system and their connection to the computer. The details of sensors used for this study can be found in Appendix.

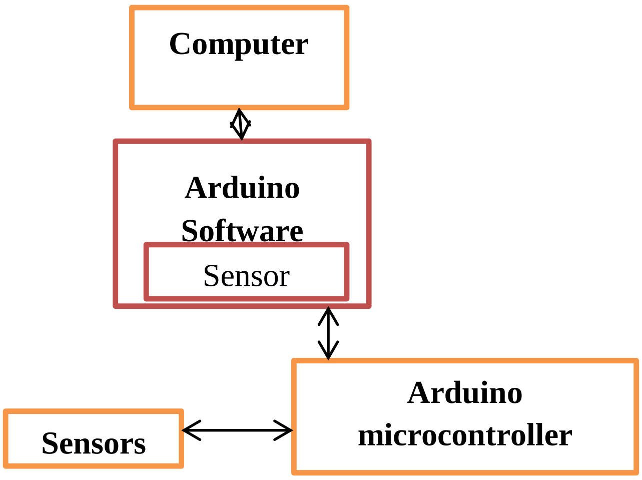

Figure 5.1: Functional arrangement of sensors and their connections with the system computer

5.4 Design of experiments

The experimental vehicles needed to comply with the requirements of the experiments in order to achieve accurate results. The driving experiments involved the sensors to sense the true state, movement angles and side and forward angles. Thus, the vehicle's movement was not controlled by automatic functions, such as the automatic balancing function performed by a hydraulic system. Therefore, the Hyundai Accent vehicle, which satisfied the experimental requirements, was selected by the researcher (Figure 5.2). KACST provided the vehicles for the experiments.

Figure 5.2: Hyundai Accent the vehicle used in the experiment.

Twenty participants were selected to perform the test-driving experiments in this project. The volunteers were divided into two main groups: Group A and Group B. Both groups had 10 participants. However, Group A was further sub-divided into five sub-groups. The first sub-group included drivers over 60 years, and the second sub-group contained drivers under 25 years. Similarly, the third sub-group consisted of new drivers that had obtained a driving license within the last two 2 years. The fourth sub-group consisted of female drivers. The fifth sub-group consisted of volunteers that had a driving license for more than 10 years.

Group B contained volunteers with the ex-criminal records in the GTD. All the drivers in this group were provided by the GTD. The drivers in this group were expert in driving and had previously demonstrated tafheet behaviour while driving, for which they had served time in prison [160].

Each group has done the experiment 3 times (20 x 3 = 60 readings) for training the system so that values for different behaviour can be concluded. Later on, the test experiment was repeated 5 times, which gave the total readings 20 x 5 = 100. The sample population used to generate the training data was low, which can affect the interpretation of results regarding the conclusion of states of behaviour. The more population could train the system very well to predict the more accurate driver’s behaviour.

It was noted that the tafheet drivers exhibited the tendency to drive at more than 100 miles per hour. However, they were cautioned not to exceed the set speed limit (60 miles per hour) during the experiment.

5.5 Safety Issue Consideration

Because of the high probability of risk involved in the driving experiments, the researcher, in conjunction with instructions given by the KACST and GDT, placed the highest priority on the safety of the participants. All necessary precautions were taken to keep the environment of the test road as safe as possible [161]. The following measures were taken.

5.5.1 Clear road

For the safety of the road user, the researcher, in consultation with KACST and GDT, decided to conduct the experiment on a straight, clear road. In this regard, GDT chose a straight clear road in a less populated area of Riyadh City. It ensured that the test road would not be a main road because they had to block both the top and the bottom of the road for use during the experiments.

5.5.2 Helmet

Helmets were an important safety precaution, especially for the tafheet drivers in Group B, who were more likely to exhibit highly dangerous tafheet behaviour during the test-driving. The driving actions of the volunteers might include sudden actions, such as moving the vehicle from side to side on the road, applying the brake pedal sharply or increasing the speed in sudden bursts. Figure 5.8 shows the helmet used by the volunteers during the test-driving.

Figure 5.3: Helmet

5.5.3 Speed concerns

Driving a vehicle at very high speeds is considered a serious criminal offence that is punished by either the suspension or the revocation of the driving license, the payment of heavy fines or imprisonment, depending on the severity of the driving offence.

Speed precautions were taken, and a safe limit of 60 miles per hour was set for the test drivers in order to observe their behaviour. The GDT did not allow the researcher to observe driving behaviour at more 60 miles per hour because they were concerned about the possibility of tafheet behaviour by the Group B participants, which could lead to serious accidents.

5.5.4 Seat belts and air bag system

The experimental vehicles used during the test-driving were all fully equipped with seat belts and an air bag system to ensure the safety of the participants in the study. According to the latest official statistical reports on traffic accidents, the seat belts and the air bag system in vehicles are fundamental in reducing casualties and fatal injuries in the event of accidents. Because the safety of the participants was the highest priority of the researcher, the selected experiment vehicles were equipped with rally seat belts and air-bag systems to provide maximum safety to the drivers. Figure 5.9 shows the rally seat belts used in the experiment vehicles.

Figure 5.4: Rally seat belts for the experiment vehicle

5.6 Obstacles and Difficulties Faced by the Researcher during the Experiments

During the experiments, the researcher faced many obstacles and difficulties, which led to some delays in the schedule. One difficulty was that it was hard to find the participants for the experiment. The participants were not punctual because they did not observe the given time schedule for experiments. Furthermore, negotiations with KACST and GDT to convince them about the experimental protocols took a great deal of time. The researcher also had to complete a plethora of paperwork before signing the collaborations with the KACST and the GDT.

In addition, some difficulties were faced when one of the experiment vehicles was damaged because one of the volunteers in Group B drove it at a very high speed. In addition, the researcher also experienced the obstacle of sand storms, which are very common in the KSA.

5.7 Summary

This chapter provided an overview of the materials and methods used to carry out the driving experiments. The researcher successfully forged two collaborations: a collaborative agreement between De Montfort University and the KACST and GDT, which was highly appreciated by both the Saudi authorities and the STRL management at De Montfort University. The collaborations are significant because in Saudi Arabia, the KACST controls all research activities and laboratories, while the GDT controls all traffic functions.

Through these collaborations, the researcher was able to select suitable vehicles and a road on which to conduct the experiments. The participants were recruited with the help of KACST. The vehicles that fit the experimental requirements were provided by KACST. The road space required for the experiments was arranged by the GDT.

Various sensors were used in this study, such as gyroscope sensors, ECG sensors and thin-film force sensors, which were installed on the base of the GL-12 Breadboard. The sensors were fitted into the OBU units of the test vehicles. During the experiments, safety precautions were taken in order to provide maximum safety to the participants. The potential tafheet behaviour of the volunteers of Group B was a particular concern. The safety precautions included helmets, seat belts, air bag systems, a set speed limit (60 miles/hour) and so on. The researcher faced several difficulties in completing these experiments; however, the data were collected successfully.

Chapter 6

Model of DBN for Driving Behaviour Detection

This chapter presents the following:

- **Problem definition to develop the DBN model for detection of Tafheet behaviour**
- **Explanation of DBN based driver's behaviour detection model**
- **Application of GeNIe 2.0 for implementation of the proposed DBN model**

6.1 Introduction

This chapter introduces a novel probabilistic framework that is capable of detecting different driving behaviours in VANET using a DBN model based on the information gathered about the vehicle, driver and the environment. The system presented here has unique feature of detecting four kinds of drivers' behaviours: tafheet, reckless, aggressive and normal based on their increasing intensity of behaviour, which was not measured by any other single driver's behaviour detection system using context aware DBN. The implementation of the system was carried out by using GeNIe 2.0. The steps followed for the development of driver's detection system are presented for this purpose are explained. Drivers' behaviour is a complex and dynamic process that evolves during the course of driving. For instance, the driver may enjoy the speed of vehicle on the road. With increased sensation and heart rate, the driver continues to speed the vehicle at higher levels unless it becomes dangerous to other users on the road. Similarly, a complex set of changes in behaviour of driver develops over the course of driving, such as changing lanes, changing vehicle angles, the to-and-fro movement of the vehicle on the road, dangerous levels of speed and in the velocity of vehicle. These effects have been observed in the case of tafheet behaviour [97]. This clearly indicates that the data on the current and previous states of drivers' behaviour are important in predicting future behaviour. In addition, the contextual information about the various states can also lead to the assessment of current driving behaviour.

Nevertheless, the design of an accurate and efficient driver behaviour detection system is a challenging task. For accuracy and improved efficiency, the system needs to have at its disposal accurate information about the temporal aspects of the driver's behaviour. The collection of data on the temporal aspects depends on the quality and accuracy of the sensors working in the sensing domain of the system. However, the sensors in the sensing phase do not also yield completely accurate information about the temporal aspects of the behaviour, which could lead to the decreased accuracy and efficiency of the behaviour detection system [9], [92]. Combining data from various sensors and building a complete picture of behaviour based on the collected information pose serious issues in developing a comprehensive driver behaviour detection system. In this regard, several data fusion methods were developed and adopted successfully by researchers. These include the as Dampester–Shaper theory, fuzzy logic, the Kalman filter and neural networks. However, these methods are unable to provide high-level capabilities in collecting uncertain contextual information or in giving complete data on various temporal aspects of the driver's behaviour.

6.2 Motivation for using DBN tool

In view of the foregoing issues and challenges, a DBN technique was used the proposed driver detection system in order to combine the data from different sensors in the sensing phase and in subsequent inferences of drivers' behaviour. The DBN technique was chosen for the following reasons. Firstly, the DBN technique is considered the most reliable method used to tackle the inaccuracies and inconsistencies associated with unobservable physical values and contextual information. Secondly, it is also considered the best method for modelling time series data, such as those obtained from the dynamic changes in drivers' behaviour. Thirdly, it is highly suitable for combining the uncertainties in the contextual information about drivers' behaviour obtained from a wide range of sensors in the sensing phase and for inferring the high-level contextual information obtained through the reasoning process about uncertain contexts. Fourthly, it is efficient in combining the data from previous nodes with the current nodes in the dynamic landscape of drivers' behaviour [11], [79], [88], [90], [91].

The DBN is formed of static Bayesian networks that are interconnected through sequential time slices (explained in Chapter 3). In designing the driver's detection system, the DBN is considered the first-order Markov, which means that the state of the hypothesis node at time slice (t) is the function of the combination of variables at time slice (t) and the state of hypothesis node at time slice (t-1). The data used to perform inferences about the driver's behaviour includes the state of the vehicle and the driver.

In summary, DBN will lead to the development of a more robust and accurate detection system designed to detect four kinds of driver's behaviour: tafheet, reckless, aggressive and normal. DBN merges the contextual information obtained from a wide array of sensors with the temporal aspects of the driver's behaviour through performing probabilistic reasoning about the uncertain context.

6.3 Problem Definition

The main objective of the design of DBN model is to deduce high-level unobservable contextual information about drivers' behaviours from the observable information gathered by sensors. The proposed model is capable of detecting four kinds of drivers' behaviour: tafheet, reckless, aggressive and normal. Drivers' behaviour is affected by multiple factors that are also called information variables. Each behaviour is represented by several observable variables or observations taken through the sensors.

Practically, it is not possible to consider all factors and their associated observations in the proposed model. Therefore, only the factors (time and time zone) and associated observations (vehicle movement angle, monitoring speed, heart beat rate, hand-grip pressure) that can facilitate the detection of the hypothesis node have been selected, which will be described in section 6.4. These factors have been selected due to the fact that time and time zone vary from country to country, therefore, set of driver's behaviour dependent on time and time zone will also vary. For example, different types of abnormal behaviour are associated with time and time zone, so the use of these factors may help the proposed driver's behaviour detection system to detect the abnormal behaviours in more effective manner. The observable factors are specifically related to abnormal behaviours, this means that they can facilitate the detection of the state of the hypothesis node accurately.

As described in Chapter 3, during the course of driving, the driver's behaviour undergoes a plethora of changes in a sequential manner. The sequence of behavioural states is connected through transition periods, which means that each state of the driver's particular behaviour lasts for a certain period before changing to the next state. The inference of the driver's behaviour is performed by merging the collected data from the contextual information and from the observable variables, as shown in Equation (6.1). Consequently, the driver's behaviour is regarded as a "current unobservable state".

In the problem domain of this thesis, the following assumptions have been made:

$[Z_1, Z_2, Z_3, \ldots.. Z_t, \ldots.]$ = a collection of endless random variables.

$$Z_t = (C_t, X_t, O_t) \qquad (6.1)$$

The above equation shows the input, hidden and output variables of behaviour detection at time slice t, where C_t and O_t are equivalents to the information and observable variables, respectively. In the above equation, X_t corresponds to the state at time t. The researcher employed a DBN to model the probability distribution over a collection of endless random variables for the inference of the current state of the driver's behaviour. In this thesis, the unrolled DBN is considered a static Bayesian network, and it is assumed that the observations of the current state at the hypothesis node are the results of immediate past time slice (t-1) and variables at the current time slice t., as follows

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i \,|Pa(Z_t^i)) \qquad (6.2)$$

6.4 Model for Driver's behaviour detection based on DBN

This section describes the steps taken to create a driver's behaviour detection model that can gather the context related data about the vehicle, the driver and its surroundings. Consequently, the driver's behaviour can be inferred over the course of driving. There are four main steps, which are explained in the subsequent sections.

6.4.1 Defining the network nodes (variables)

In the first step of creation of DBN model for detection of driver's behaviour, the nodes in the network have been specified and along with determination of the associated states for each node or variable. DBN model can process both continuous and discrete variables. However, the discrete variables were chosen for building the model, which does indicate that they have finite set of values.

Current state of the driver is specified as a hypothesis node in the proposed DBN network, whilst the contextual nodes associated with the hypothesis node are divided into two groups. The first group represents the set of information nodes affecting the hypothesis node, and it constitutes the part of the input information. The second group corresponds to the observable nodes and represents the information emanating from the hypothesis nodes, thus forming part of the output information.

Group 1

This group of nodes contains contextual information such as circadian rhythm, which can affect the hypothesis node.

> **Circadian rhythm**: This represents the information derived from the human sleep–awake cycle, which corresponds to the driver's active or passive state on the road during driving. There are two periods during a day and a night when tafheet drivers are considered in the most active state (11 a.m.–17 p.m. and 20–22 p.m.) [11], [79], [162]. Therefore, during these peak periods, tafheet behaviour of drivers can reach a peak state, which can influence the hypothesis node in the proposed network. The circadian node is influenced by two nodes: time zone and time nodes. Hence, the circadian and its associated nodes (time and time zone) constitute the contextual information nodes in the DBN network in proposed this thesis.

Group 2

This group of nodes represents the contextual variables originating from the hypothesis node. It provides information relating to the states of vehicle (angular movement of vehicles etc.) and the states of the driver (heartbeat, handgrip pressure etc.).

Vehicle angular movement: This movement represents the movement of vehicles and their orientation on the road [126]. The wheels make an angle with road while moving on the road. This angle is measured by the pitch, roll and yaw sensors to sense the movement of the vehicle in a three-dimensional space.

Monitoring speed: This variable provides information about changes in states of speed, which are recognized by the speed sensor from the GPS.

Heartbeat rate: This is an important variable because when the driver goes into an excited and sensational state while driving the car, he or she may show abnormal behaviours, such as aggressive, reckless, tafheet and so on.

Handgrip pressure: The handgrip pressure is included in this study as an important variable used to detect tafheet behaviour. During tafheet behaviour, the handgrip of the driver tightens extremely on the steering wheel, which is the reason that it is a characteristic of abnormal behaviour.

After specifying the hypothesis, information and observable nodes, the discrete states of each node must be determined before the selection of probability value for each state in the network. Tables 6.1, 6.2 and 6.3 provide the discrete values assigned to all chosen nodes in the proposed DBN.

Node Name	State 1	State 2
Monitoring_Speed	Good (<80 mph)	Bad (>80 mph)
Heart_beat	Normal (	Abnormal
Hand_Grip_Pressure	standard	Nonstandard

Vehicle_Movement_Angle	Normal	Abnormal
Roll	Normal	Abnormal
Pitch	Normal	Abnormal
Yaw	Normal	Abnormal

Table 6. 1:Observable nodes and their states

Node Name	State 1	State 2
Time	Tafheet	Normal
Time_zone	Change	No_change
Circadian	Tafheet	Normal

Table 6. 2: Information nodes and their states

Hypothesis node	State 1	State 2	State 3	State 3
State	Normal	Reckless	Aggressive	Tafheet

Table 6. 3: The states of the hypothesis node

In the table 6.1, the states of the monitoring speed variable depends on the speed zone of each road (motorway, city areas etc). For example, on the motorway, the 'good' speed of vehicle is less than 80 mph, while the speed above 80 mph has been taken as 'bad'. Similarly, the normal heart beat rate depends on the driver's age, medical condition and speed of the vehicle. The heart beat rate 60-100 beats/minute has been taken a normal while the heart beat rate >100 beats/minute or <60 beats/minute have been considered to be abnormal during the experiments conducted in this study. The behaviour of driver is complex and may exist in multiple states. In order to avoid complexity and confusion to interpret the results of this study, the state of each variable has been restricted to only two states (good, bad, normal, abnormal).

6.4.2 Drawing the network graph

The 2nd step in creating the DBN model is to draw the network graph, which can be done by assigning causal relationships between the variables, which are normally represented by drawing the network arcs. Drawn in this way, the graph denotes the directed acyclic graph, which is characteristic of the DBN model. Figure 6.1 shows the proposed DBN model which can detect driver's abnormal behaviour such as reckless, aggressive and tafheet. IN the proposed model, the state nodes is equivalent to the hypothesis node in the network. The variables on the top layer of the state node represent the information variable or nodes, whilst the variables shown below the state node are the observable variables. In Figure 6.1, the DBN network is unrolled for two time slices: *t* and *t-1*. The state at time slice *t* depends on the variables at time slice *t* and the state of the observable node at time slice *t-1*. The same pattern can be replicated for all other time slices in the DBN network.

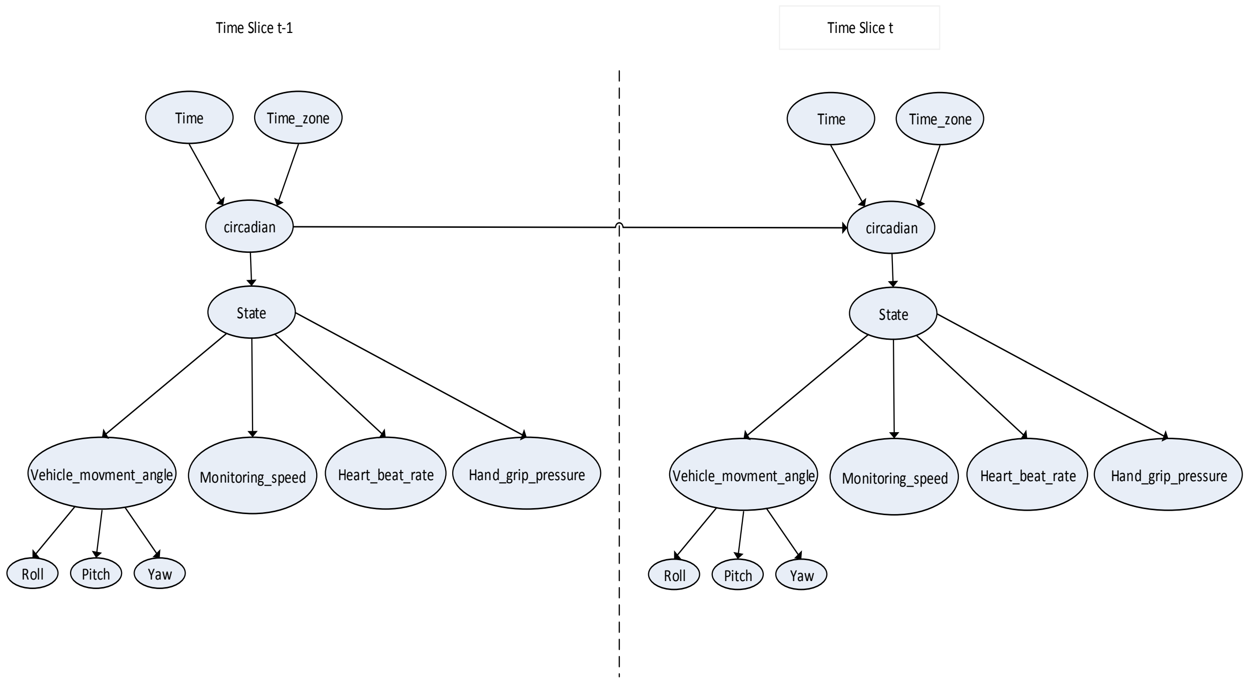

Figure 6.1: A DBN model for detecting drivers' behaviour

6.4.3 Parameterising the network

After specifying the variables or nodes within a DBN network, the next step is to parameterise the network, in which conditional probability values and their presentation in CPT tables are assigned to each node in the network. At this stage, the prior probability values are assigned to each root node, followed by the conditional probabilities values for their links. The process of defining the probability of nodes in the network indicates the chance of each node being in one of the probable states after the evidence is received. As explained in Chapter 3, this process can be done either by collecting the huge amount of training data and subsequent performance of complex statistical analysis on it or by analysing the previously published data on the same or a similar system.

For the proposed model in this thesis, the values for conditional probability and transition distribution tables for two time slices were derived from the analysis of the experimental data by observation the drivers behaviours for training the system. Tables 6.4 to 6.14 show the prior probability values and conditional probability values for all the variables in the network.

Time	Probability
Tafheet	0.08
Normal	0.92

Table 6. 4: Prior probability for Time node

Time_Zone	Probability
Change	0.17
No_change	0.83

Table 6. 5: Prior probability for Time zone node

Time / state	Time_Zone	Circadian	Probability
Tafheet	Change	Normal	0.9
	No_change	Normal	0.3
	Change	Tafheet	0.1
	No_change	Tafheet	0.7
Normal	Change	Normal	0.4
	No_change	Normal	0.9
	Change	Tafheet	0.6
	No_change	Tafheet	0.1

Table 6. 6:Conditional probabilities for Circadian node given its parents

Circadian	State	Probability
Normal	Normal	0.40
	Reckless	0.36
	Aggressive	0.19
	Tafheet	0.05
Tafheet	Normal	0.24
	Reckless	0.31
	Aggressive	0.26
	Tafheet	0.19

Table 6. 7: Conditional probabilities for State node at time (t-1) given its parents

Monitoring_Speed / state	Normal	Reckless	Aggressive	Tafheet
Good	0.95	0.4	0.16	0.05
Bad	0.05	0.6	0.84	0.95

Table 6. 8: Conditional probabilities for Monitoring_Speed node given its parent

Heart_beat / state	Normal	Reckless	Aggressive	Tafheet
Normal	0.96	0.69	0.86	0.01
Abnormal	0.04	0.31	0.14	0.99

Table 6. 9: Conditional probabilities for Heart_beat node given its parent

Hand_grip_pressure / state	Normal	Reckless	Aggressive	Tafheet
Standard	0.5	0.2	0.75	0.98
Nonstandard	0.5	0.8	0.25	0.02

Table 6. 10: Conditional probabilities for Hand_grip_pressure node given its parent

Vehicle_movement_angle / state	Normal	Reckless	Aggressive	Tafheet
Normal	0.98	0.46	0.82	0
Abnormal	0.02	0.54	0.18	1

Table 6. 11: Conditional probabilities for Vehicle_movement_angle node given its parent

Roll / Vehicle_movement_angle	Normal	Abnormal
Good	0.95	0.98
Bad	0.05	0.02

Table 6. 12: Conditional probabilities for Roll node given its parent

Pitch/ Vehicle_movement_angle	Normal	Abnormal
Good	0.92	0.07
Bad	0.8	0.93

Table 6. 13: Conditional probabilities for Pitch node given its parent

Yaw / Vehicle_movement_angle	Normal	Abnormal
Good	0.94	0.07
Bad	0.06	0.93

Table 6. 14: Conditional probabilities for Yaw node given its parent

6.4.4 Inferring the hypothesis node (variable)

Inferring the hypothesis node constitutes the last step in designing the proposed DBN network. During this process, the current state of the hypothesis node is determined by applying the reasoning process involving the data collected from the information node affecting the current state and the information gathered from the observable variables at a particular time slice.

As explained in Chapter 3, the inference in DBN can be performed through either the conversion of a DBN to a HMM followed by carrying out a forward-and-backward algorithm or unrolling the DBN network and application of any exact static algorithm. However, the latter method was applied in this thesis to infer the hypothesis node. In the proposed network, the state of the hypothesis node is the product of the states of both the information and the observable nodes. Therefore, the combined reasoning process facilitates the performance of an effective inference at the state node (hypothesis node). The polytree algorithm satisfies the above criteria for inference because it works with the information collected from both parent and children nodes in the network, which is the reason that it was selected to perform the inference at the state node in the proposed DBN network [167].

Figure 6.2 shows the unrolled DBN model for T time slices (similar used in [169]). The hypothesis node at the previous time slice (x_{t-1}^{l}, where l = 1, 2, 3, 4….) acts as the information node for the hypothesis node at the current time slice t.

Let us assume

Xt = state node or hypothesis node at the current time slice t

$C_t^j = information\ variables\ at\ time\ t, where\ j = 1, 2, 3, \ldots ....$

$O_t^k = observable\ variables\ at\ the\ current\ time\ slice\ t, where\ k = 1, 2, 3, 4, 5, 6, 7$

x_t^l = values taken by Xt

$c_t^{j,m}$ = values taken by C_t^j

$o_t^{k,n}$ = values taken by O_t^k

e_t^- = evidence received from node X's children = $\{e_{o,j}^{i,j}\}$ = the evidence with *i*th observable node with *j*th state at current time slice t.

e_t^+ = evidence received from node X's parents = $\{e_{c,j}^{i,j}\}$ = the evidence with *i*th information nodes with *j*th states at current time slice t.

$e_t = \{e_t^-, e_t^+\} = The\ evidence\ at\ the\ current\ time\ slice\ t$

Based on the above assumptions, the conditional probability of the hypothesis node at the current time slice t can be calculated using the polytree algorithm in the following equation,

$$P(X = x_t^l | e_t) = \alpha.\lambda(X).\pi(X) = \frac{\lambda(X).\pi(X)}{\sum\limits_{x^l} \lambda(X).\pi(X)} \qquad (6.1)$$

$$l = 1, 2, 3, 4$$

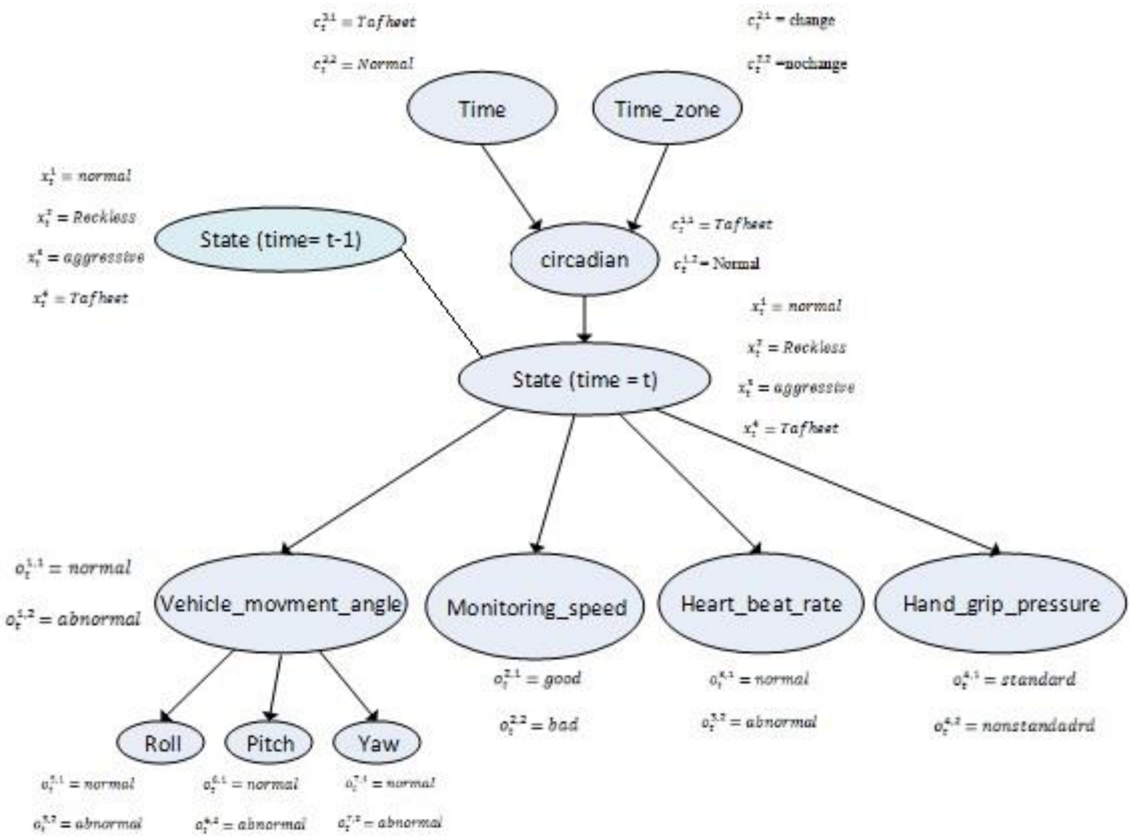

Figure 6.2: Overview of an unrolled DBN fragment

where

$\lambda(X) = P\ (e_t^-|X)$ represents the conditional probability evidence gathered from the observable nodes at hyposthesis node at current time slice t

Subsequently, the above equation (6.1) can be presented as follows:

$$P\left(X = x_t^l \middle| e_t\right) = \frac{P(e_t^-|X = x_t^l)\,.\,P(X = x_t^l|e_t^+)}{\sum_{i=1}^{4} P\left(e_t^- \middle| X = x_t^j\right).\,P(X = x_t^j|e_t^+)} \qquad (6.2)$$

L = 1, 2, 3, 4

The value of P $(e_t^- | X = x_t^l)$ can be calculated by the following equation

$$P\left(e_t^- \mid X = x_t^j\right) = \prod_{i=1}^{5} \lambda_{O_t^i}(X)$$

$$= \left(P\,(e_{0,t}^{1,j} \setminus \mathrm{X} = x_t^j\,)\right) \times \left(P\,(e_{0,t}^{2,j} \setminus \mathrm{X} = x_t^j\,)\right) \times \left(P\,(e_{0,t}^{3,j} \setminus \mathrm{X} = x_t^j\,)\right)$$

$$\times \left(P\,(e_{0,t}^{4,j} \setminus \mathrm{X} = x_t^j\,)\right) \times \left(P\,(e_{0,t}^{5,j} \setminus \mathrm{X} = x_t^j\,)\right) \qquad (6.3)$$

The value of P $(\mathrm{X}|e_t^+)$ in equation (6.3) can be calculated by the following equation(6.4)

$$P\left(X = x_t^l \middle| e_t^+\right)$$

$$= \sum_{c_t^1, c_t^2, x_{t-1}} P\left(X = x_t^l \middle| c_t^1, c_t^2, x_{t-1}\right) \prod_{i=1}^{3} \pi_X\,(c_t^j)$$

$$= \sum_{i=1}^{2} \sum_{m=1}^{2} \sum_{n=1}^{4} P\left(X = x_t^l \middle| c_t^{1,i}, c_t^{2,m}, x_{t-1}^n\right). P\left(c_t^{1,i} \middle| e_{c,t}^{1,2}\right). P\left(c_t^{2,m}\right). P(x_{t-1}^n) \quad (6.4)$$

Hence, the above equations 6.2, 6.3 and 6.4 can be used to obtain the values for the conditional probability of the hypothesis node at the current time slice t. This was performed during the inference process on the information node at the previous time slice t-1 and on the observable nodes at time slice t.

6.5 Threshold of decision making

The proposed DBN model for driver's behaviour detection makes the decision based on the data collected from the sensors. The data may be within the alarming range to show that the detected behaviour is true or false. The definitions of two bounds is important that it will be easy for the user to define the two boundaries of values between which the probabilities in CPT can vary and still can be considered to be correct. The sensitivity function

$$P\ (x_r^n\ |e_n)\ (\theta) \qquad (6.6)$$

need to be applied in order to compute the variations between two values without having any change in the decision of the proposed DBM model for detection of aggressive, reckless and tafheet behaviour. The equations for the upper and lower bounds can be written as below:

The sensitivity function = $\frac{p\ (x_r^n\ ,e_n)(\theta)}{P(e_n)(\theta)} = P^- \ and\ \frac{p\ (x_r^n\ ,e_n)(\theta)}{P(e_n)(\theta)} = P^+$ (6.7)

The sensitivity function given in the above equations will give the values for higher order polynomials. Unlike the decision-making process of BNs, there is no assurance that above functions will show either the non-increasing or non-decreasing values. Therefore, the foregoing equations may represent the multiple solutions which cannot be taken as standard threshold values as the proposed DBN makes the decision based on the likelihood of the driver's behaviour. For example, the system will predict that tafheet behaviour will be 80% likely to happen at the degree of belief presented in the tables 7.1

and 7.2. Therefore, it is not possible to define the threshold values for the DBN system which works in the uncertain environment [186].

6.6 Application of GeNIe 2.0 for Implementation of the Proposed DBN Model

GeNIe 2.0 is a well-known tool used for the implementation of DBN models [127], [129], [142]. It was originally designed by the group of researchers at the University of Pittsburgh. The unique features of this software are designed to support the implementation of process of both BN and DBN models. Moreover, this software is the only source of powerful temporal reasoning process, and it supports different types of inference algorithms, which enables the performance of inferences on the hypothesis node in the proposed network. The following sections will provide an overview of the use of GeNIe 2.0 for building the DBN model in this thesis.

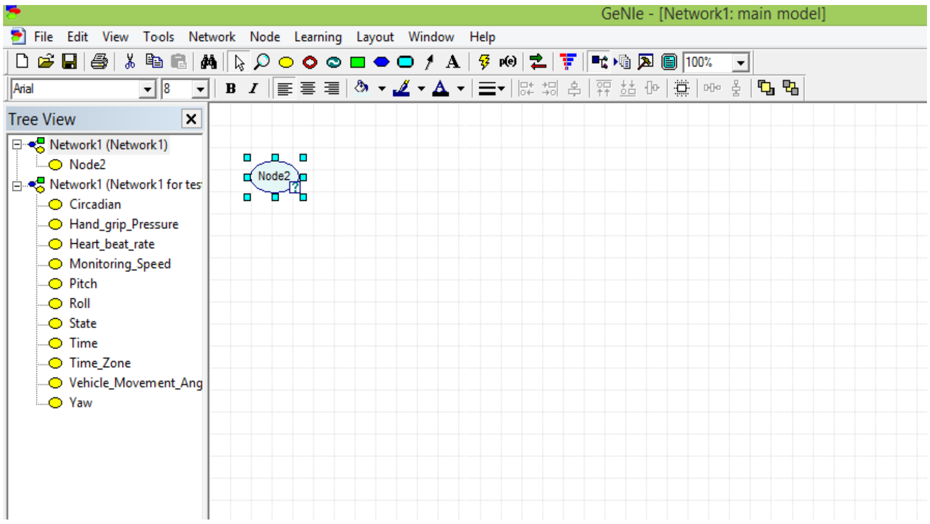

Figure 6.3: Overview of GeNIe 2.0

6.6.1 Creating network nodes

Two types of nodes are normally used to create network: temporal and static nodes. The temporal nodes are used in building the DBN network because they can change their values over time. In the first step, the temporal plate is inserted, and in the second step, the temporal nodes are inserted in the place. The insertion of the temporal plate into the GeNIe 2.0 environment is shown in Figure 6.4.

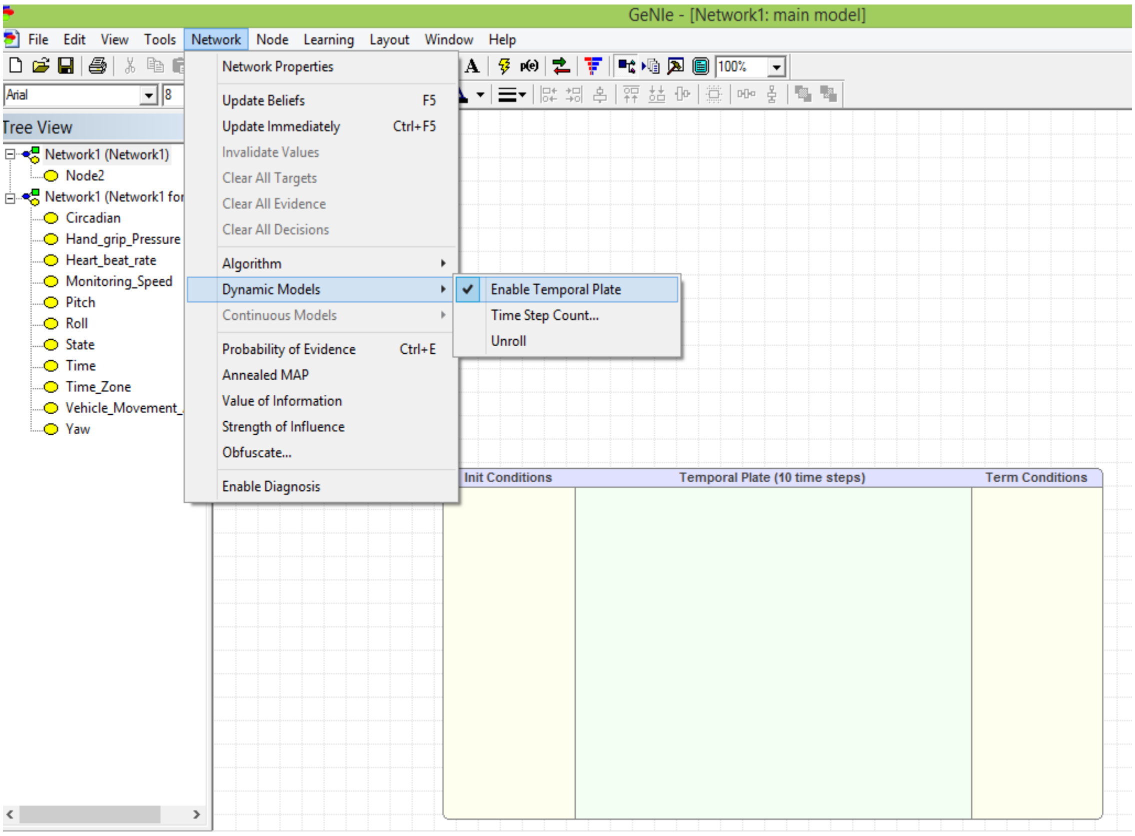

Figure 6.4: Insertion of temporal plate in GeNIe 2.0 environment

The placement of the temporal plate divides the working environment of GeNIe 2.0 into four sections, which are described below:

Temporal plate: The network nodes in the temporal nodes can be updated, and their values can be inserted and developed as can be seen in figure 6.5. Furthermore, the time-slices within this plate can be changed through double-clicking on them, based on the number of time slices required for the inference process.

Contemporals: These nodes are also called static nodes that remain steady over time, and their values need to be inserted whenever the values need to be changed.

Initial nodes: In this environment, only nodes from the first time slice are inserted during the inference process.

Terminal conditions: This requires the nodes to be inserted from the last or terminal time-slice in the network during the inference process.

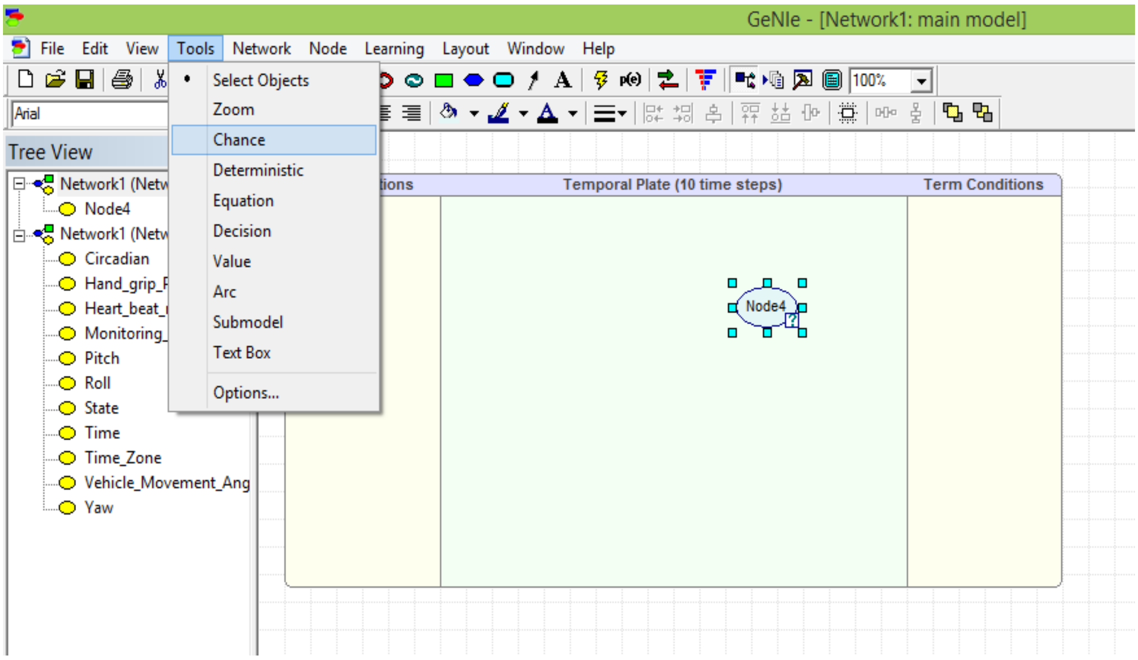

Figure 6.5: Method of inserting nodes in temporal plate in GeNIe

Following the insertion of the temporal plate, the nodes of a DBN are inserted into the plate. This is done by clicking on *Chance*, selecting the *Chance* option from the drop-down menu and then clicking inside the temporal plate to add a node in the given space, as shown in Figure 6.6. Once node has been created; its name, type and states can be specified by clicking nodes in the main menu bar.

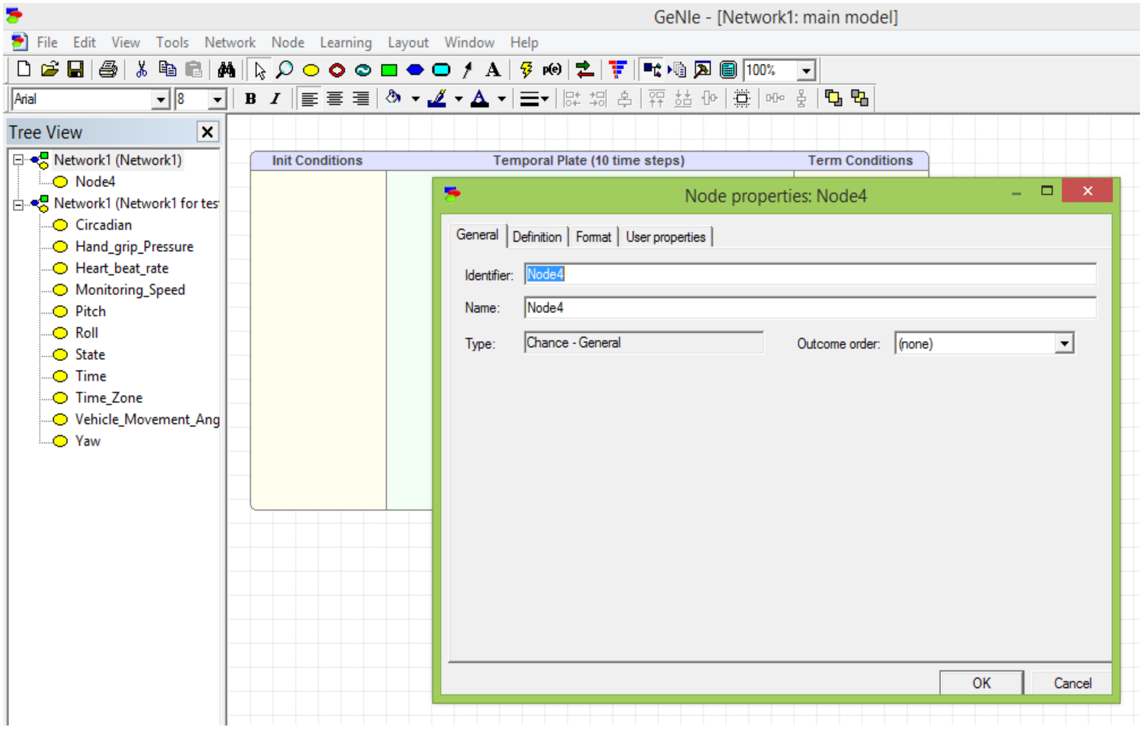

Figure 6.6 : Method used to specify the node properties in GeNIe

6.6.2 Creation of network-arcs and conditional probability tables

Networks arcs are drawn to define the casual relationships between various nodes in the network. Two types of arcs are found in GeNIe 2.0: normal arcs and temporal arcs. The former defines the casual relationship between the nodes located within a single time slice, and the latter does the same for nodes located in two consecutive time slices. The networks arcs are added by clicking the *Tools* option in the main menu bar, selecting the parent or child node category and then choosing either normal or temporal arcs. The pop-up window will show the option *order of arc*, which means the temporal time slice to which the specific arc belongs. For example, order 1 indicates that the node depends on the state of the node in the previous time slice (first-order Markov process). In our network, the hypothesis node depends only on the state of its immediate node; the temporal arc of the hypothesis node is set to *order 1*. The action of inserting networks shown in the following figure 6.7:

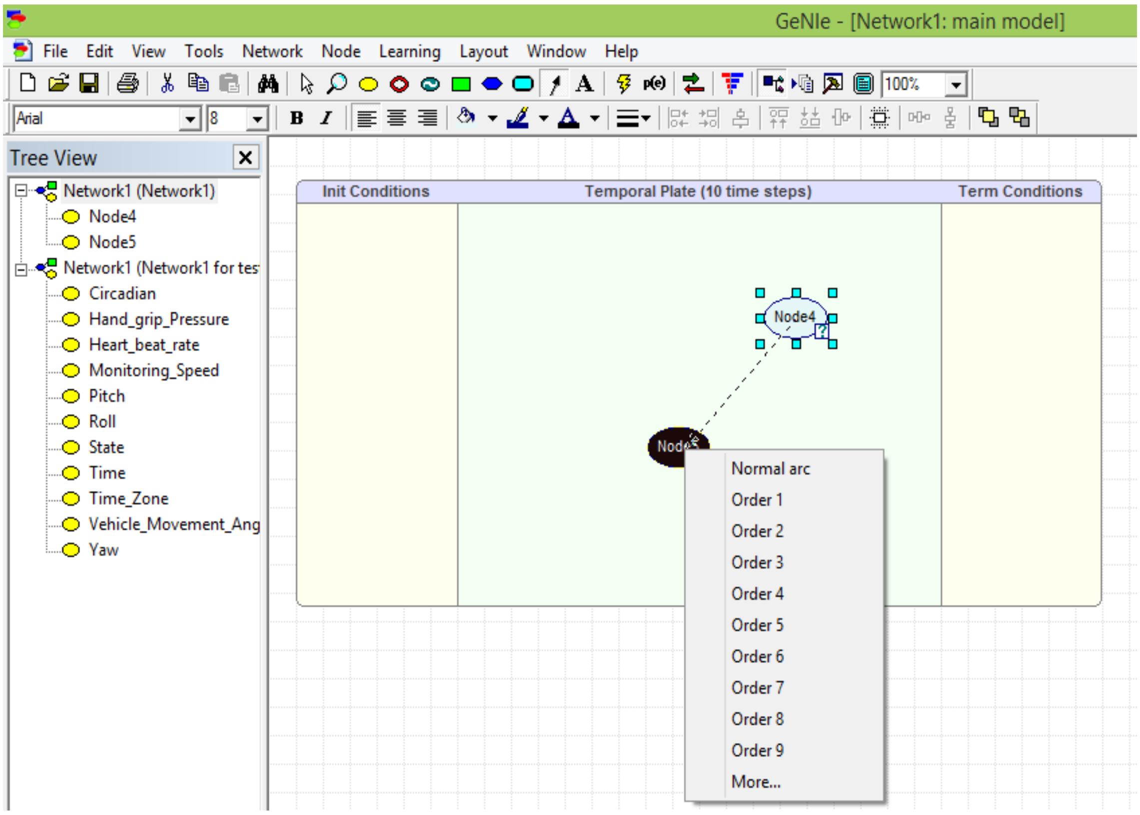

Figure 6.7: Addition of networks arc in GeNIe

Following the drawing of the network arcs, the values of CPT for all nodes in the network are added. This is done by double-clicking the node and selecting the definition tab in the main menu bar. The values of conditional probability distributions are then entered into the fields designated by the states of the variable.

6.6.3 Accessing the experimental data

This thesis used the experimental data for the inference and the analysis. The data were accessed from the external database in the computer. GeNIe 2.0 gives the option to access data from the folders in the computer. The data on the 20 volunteers who participated in this study were first converted into a text document format that was suitable to be transferred to the GeNIe environment. Following the preparation for access, the file option in the main menu bar was selected. In the drop-down menu, the option *Open Data File* was clicked to transfer the relevant data text file documents into GeNIe 2.0.

6.6.4 Discretization of the data

The data collected by the researcher during experiments was in continuous format. However, GeNIe 2.0 does not process the continuous forms of data. Therefore, the data were converted into a discretinized form by double-clicking the selected column and clicking the discretization option in the drop-down menu. This caused the pop-up window to appear, which provided instructions on discretizing the data in the columns as shown as an example in figure 6.8. The data were subjected to the *learning network* option in the *Network* option in the main menu bar.

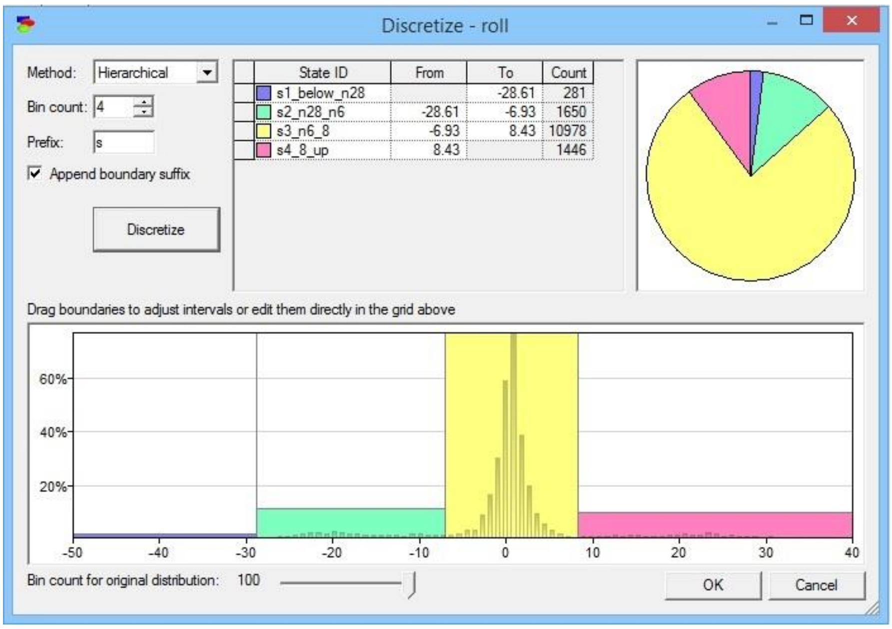

Figure 6.8: Discretization of data in GeNIe 2.0

6.6.5 Inference and outcomes

GeNIe 2.0 supports various algorithms that are executed on data. The choice of algorithm depends on the researcher's aim in the analysis. The polytree algorithm was selected for the current analysis, which was explained in Chapter 3. The selection of the desired algorithm was performed by clicking on *Network* and selecting the type of *algorithm* from the drop-down menu. The inference was then carried out by clicking on the network area and choosing the option *Update Beliefs*. The updated beliefs of the network nodes can be obtained by simply clicking on the state node and then choosing the *value* tab. This action is shown in Figure 6.9.

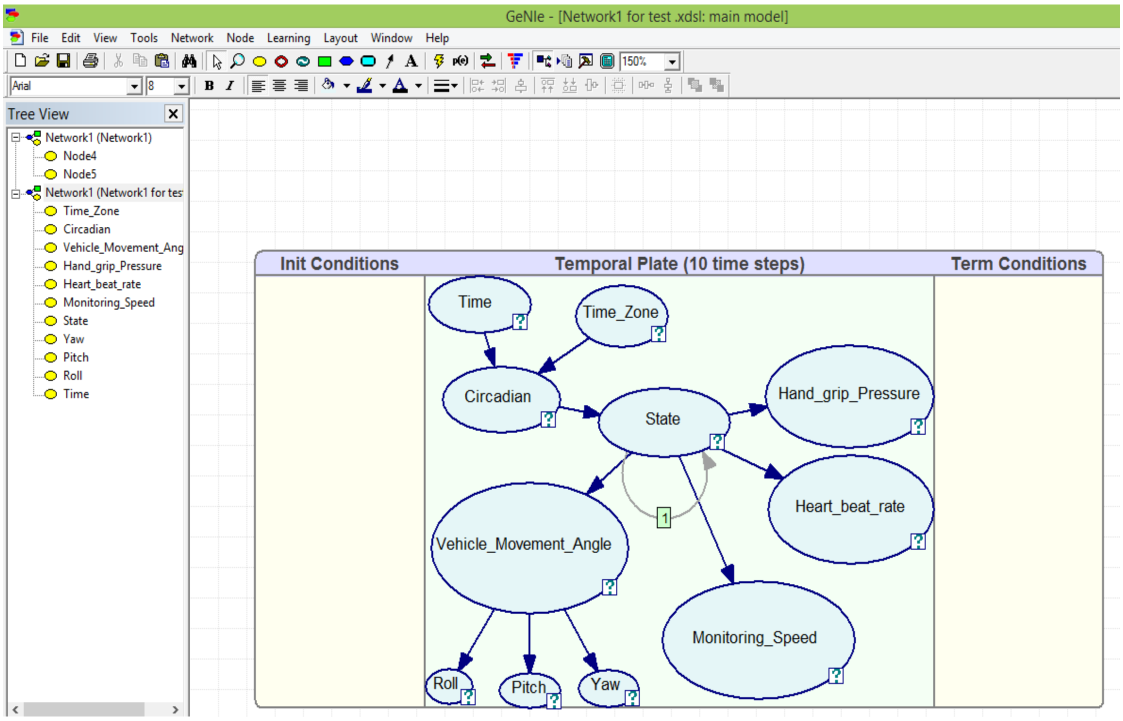

Figure 6.9: DBN structure implemented by GeNIe

6.7 Summary

A novel driver behaviour DBN detection model was presented in this chapter. The DBN model was able to detect different styles of drivers' behaviour, such as tafheet, normal, reckless and aggressive, which is a further step towards improving the safety of passengers on the road. The chapter provided theoretical insight into the function of the proposed DBN model regarding reasoning the contextual data derived from many variables related to the vehicle and the driver and performing probabilistic inference to detect drivers' behaviour.

When the DBN model was unrolled for the individual time slices in order to study the connections among variables, each unrolled DBN model acted as a static Bayesian network. Its state was influenced by the state of the hypothesis node in the previous network. Hence, the hypothesis node from the previous time slice served as an information node for the hypothesis node in the current time slice. After the parameterization of the proposed network, the polytree algorithm was selected to execute the inference process on the hypothesis node to deduce the driver's behaviour. GeNIe 2.0 and its application to build the proposed network were described in the last section of this chapter.

The next chapter will elucidate the evaluation and validation of the proposed model by using the experimental data for the detection of drivers' behaviour. Furthermore, the outcomes will be supported by the presentation of case studies to verify the accuracy and validity of the DBN model.

Chapter 7

System Evaluation and Case studies

This chapter presents the following:

- Validation of the proposed DBN model
- Description of the evaluative procedure used to identify the effects of observable nodes on the hypothesis node
- Validity of the proposed DBN model for the detection of tafheet behaviour
- Case studies to show the accuracy and validity in identification of tahfeet, aggressive and reckless behaviours

7.1 Introduction

The detection of the abnormal behaviour of drivers during driving is essential to prevent accidents and fatalities from occurring on the road. The chapter presents the validation of the proposed DBN driver's behaviour detection model using the experimental data, by focusing on the ability and accuracy of the system to detect abnormal behaviour. The chapter explains that the proposed DBN model is effective and accurate in terms of detecting all four styles of driving behaviour: normal, reckless, aggressive and tafheet.

In the first section, different combination of evidence that was gathered from both the information and observable nodes are used to validate the system. This section also explains the accuracy of the system and the ability of system to detect all four behaviours. This is followed by determining the effects of both the information and observable nodes on the state node (hypothesis node).

Furthermore, three case studies are presented in the last part of this chapter to show the performance and the validity of the DBN driver's behaviour detection model. Each case study is supported by scenarios on the road, which use different combinations of evidence gathered from the information and observable nodes. The first case study shows the ability of the system to detect tafheet behaviour; the second case demonstrates the accuracy and validity of the system in detecting aggressive behaviour; and the third case study illustrates the capability of the system to detect reckless behaviour using different combinations of evidence.

7.2 Validation of the Proposed Model

The proposed system was validated by using all possible combinations of the evidence received from the sensors. Based on the parameterized DBN, the system starts to perform inferences on the driver's behaviour data received from various sensors in the sensing phase. The proposed network consists of eight nodes, including the root and leaf nodes. Each node consists of two possible phases or states. Therefore, the total number of possible combinations of all evidence received is equal to 2^8. The circadian node was treated as an evidence node because it is affected by time and time zone as sexplained in chapter 6. Similarly, vehicle angular movement was also regarded as evidence because it affects three states: yaw, pitch and roll. After considering vehicle angular movement, monitoring speed, heartbeat rate, handgrip pressure, the total amount of possible evidence collected from the observable nodes is equal to 2^5 = 64 inputs. During the inference process conducted at time slice t, the hypothesis node was affected by variables at the hypothesis node at t-1 time slice, as well as by the information and observable variables.

All possible combinations of evidence are presented in Tables 7.1 and 7.2. In order to cover the hypothesis node at current and previous locations, two time slices t (current) and t-1 (previous) were considered during the evaluation of the proposed DBN model. The following abbreviations were used for the nodes in DBN for the sake of simplicity.

VAM = vehicle angular movement

MS = monitoring speed

HBR = heartbeat rate

HGP = hand grip pressure

No	VMA	MS	HBR	HGP	State	Degree of Belief
1	Normal	Good	Normal	Standard	normal	0.86148389
2	Normal	Good	Normal	nonstandard	normal	0.79821242
3	Normal	Good	abnormal	Standard	normal	0.49956663
4	Normal	Good	abnormal	nonstandard	reckless	0.67297643
5	Normal	Bad	Normal	Standard	aggressive	0.80646933
6	Normal	Bad	Normal	nonstandard	reckless	0.57703358
7	Normal	Bad	abnormal	Standard	aggressive	0.70101641
8	Normal	Bad	abnormal	nonstandard	reckless	0.81828623
9	Abnormal	Good	Normal	Standard	reckless	0.59164279
10	Abnormal	Good	Normal	nonstandard	reckless	0.90045212
11	Abnormal	Good	abnormal	Standard	reckless	0.50050133
12	Abnormal	Good	abnormal	nonstandard	reckless	0.9777595
13	Abnormal	Bad	Normal	Standard	aggressive	0.54766147
14	Abnormal	Bad	Normal	nonstandard	reckless	0.90096155
15	Abnormal	Bad	abnormal	Standard	Tafheet	0.87835583
16	Abnormal	Bad	abnormal	nonstandard	Tafheet	0.91492734

Table 7. 1: First set of combinations of evidence

Table 7.1 illustrates the sates of observable nodes, the inference results (state node) and the degree of belief, given that Circadian node = Normal

No	VMA	MS	HBR	HGP	State	Degree of Belief
1	Normal	Good	Normal	Standard	Normal	0.78214207
2	Normal	Good	Normal	nonstandard	Normal	0.73423839
3	Normal	Good	abnormal	Standard	Normal	0.38567227
4	Normal	Good	abnormal	nonstandard	Reckless	0.71412878
5	Normal	Bad	Normal	Standard	aggressive	0.77243331
6	Normal	Bad	Normal	nonstandard	Reckless	0.51685529
7	Normal	Bad	abnormal	Standard	aggressive	0.86874567
8	Normal	Bad	abnormal	nonstandard	Reckless	0.76541222
9	Abnormal	Good	Normal	Standard	Reckless	0.56509301
10	Abnormal	Good	Normal	nonstandard	Reckless	0.90676194
11	Abnormal	Good	abnormal	Standard	Tafheet	0.64698797
12	Abnormal	Good	abnormal	nonstandard	Reckless	0.96842798
13	Abnormal	Bad	Normal	Standard	aggressive	0.61692424
14	Abnormal	Bad	Normal	nonstandard	Reckless	0.86566928
15	Abnormal	Bad	abnormal	Standard	Tafheet	0.94414607
16	Abnormal	Bad	abnormal	nonstandard	Tafheet	0.83409245

Table 7. 2: Second set of combinations of evidence

Table 7.2 illustrates the sates of observable nodes, the inference results (state node) and the degree of belief, given that Circadian node = Tafheet state

It is evident from the above tables that system is able to detect various states of driver such as normal, Tafheet, reckless and aggressive accurately, when all set of possible combinations of evidences are applied. This further demonstrated that system is accurate and valid in terms of detecting different driver's behaviour, and different combination of evidence gives the different states with various degrees of belief.

7.3 Validity of the Detection of Tafheet Behaviour

The system was able to detect reckless behaviour accurately after the experimental data were put into GeNIe 2.0. The data analysis was performed through the "learning parameters" command in the software, which sorted the data into three categories based on the probability values of reckless, aggressive and tafheet behaviour. These values were provided to the DBN model built in GeNIe 2.0. The system displayed graphs of all drivers in the experiment, which clearly showed when the drivers were in normal, reckless, aggressive and tafheet states.

For instance, the model showed that the approximate yaw angles (in degrees) recorded by the yaw sensors for the normal driving behaviour were about 42–44^0 on the straight road chosen for the test experiments, as described in Chapter 5. The values above and below that limit were considered abnormal. The degree of abnormality was supposed to increase as the limits of normal vehicular yaw angles were exceeded.

For example, for test driver 12, the yaw sensor readings analysed by the system showed a vehicular forward-angular movement in the range of 44–75^0 (above the normal limit) and 42–28^0 (below the normal limit). A huge difference was observed between the ranges of the observed and the normal values, which indicated that the test driver was very close to showing tafheet behaviour, as shown in Figures 7.4 and 7.5.

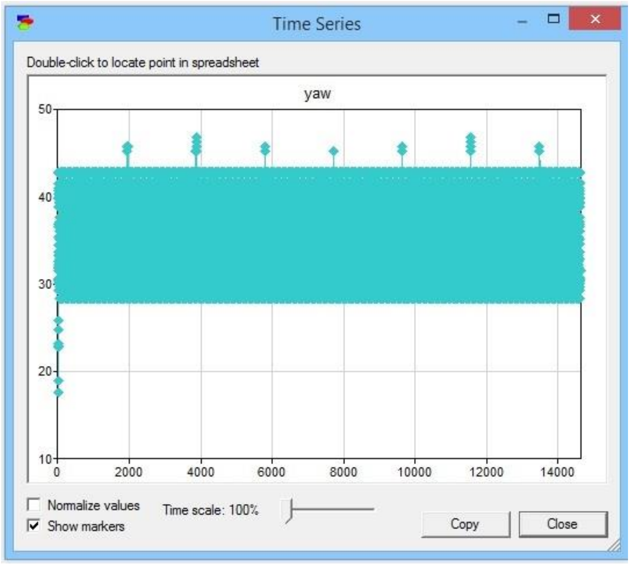

Figure 7.1: Yaw data for normal behaviour

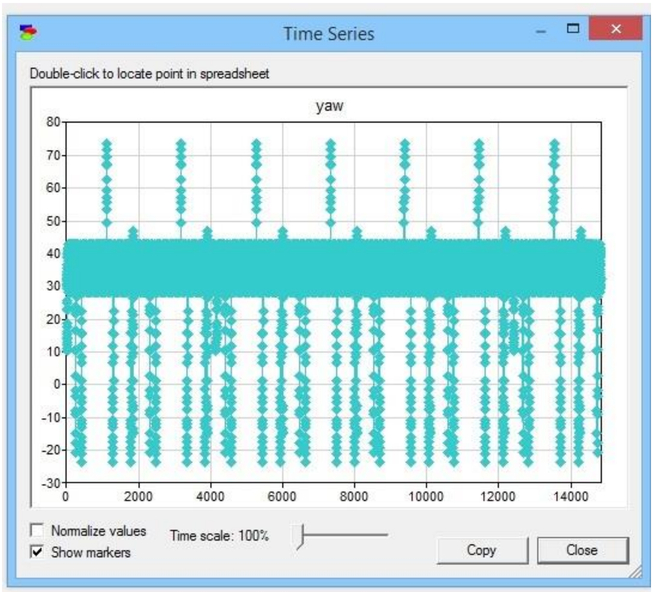

Figure 7.2: Yaw data for abnormal behaviour

Similarly, the roll angle range recorded by the roll sensor in the gyroscope for normal use lies in the approximate range of 5.5 to -3.8 degrees, as shown in Figures 7.6 and 7.7. Any values recorded by the roll sensor below or above the normal range were considered in the abnormal range, thus confirming the abnormal behaviour of the user. For instance, in the real time experiments, test driver 12 showed dangerously abnormal behaviour (tafheet behaviour) with a roll range between 5.5 and 40 degrees (above the normal limit) and -3.8 to -40 degrees (below the limit), as shown in Figures 7.6 and 7.7. The findings clearly indicated that the driver was more likely to show tafheet behaviour.

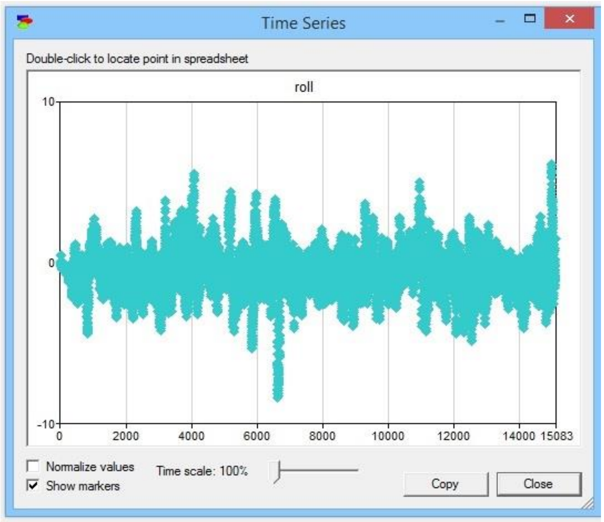

Figure 7. 3: Roll data for normal behaviour

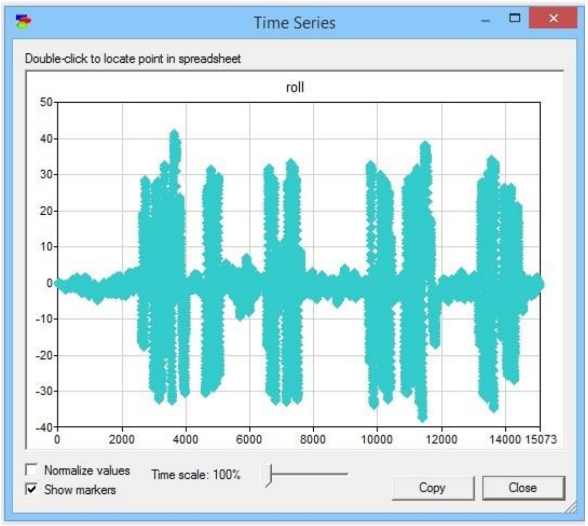

Figure 7.4: Roll data for abnormal behaviour

The same range was determined for the normal and abnormal behaviour of the test driver by using data from the pitch sensor of the gyroscope, as shown in the Figures 7.8 and 7.9. Any readings taken by the pitch sensor above 8^0 and below -9^0 were considered to show the abnormal behaviour of the driver. Test driver 12 showed pitch angle values below the marked range of -9^0 to -24^0 and above the marked range of 10^0-18^0.

It was observed that test driver 12 showed abnormal values of pitch, roll and yaw angles, which were recorded by the pitch, roll and yaw sensors, respectively. The analysis of these data showed that this user exhibited tafheet behaviour, which was confirmed by the subsequent implementation of the DBN model, shown in Tables 6.1 and 6.2.

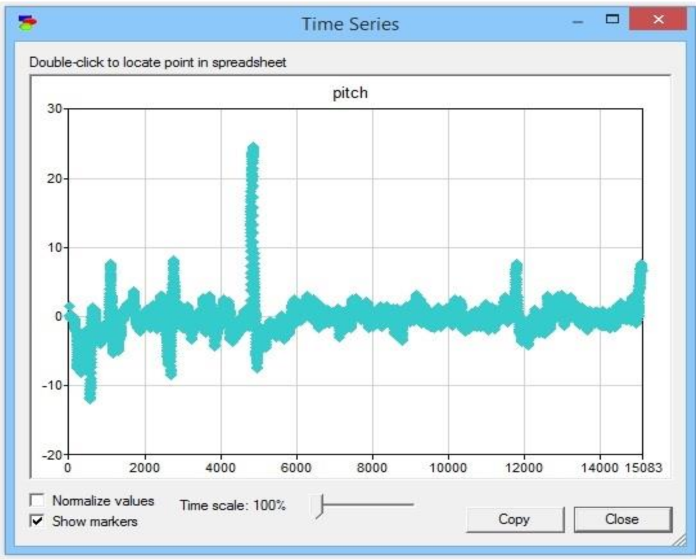

Figure 7. 5: Pitch data for normal behaviour

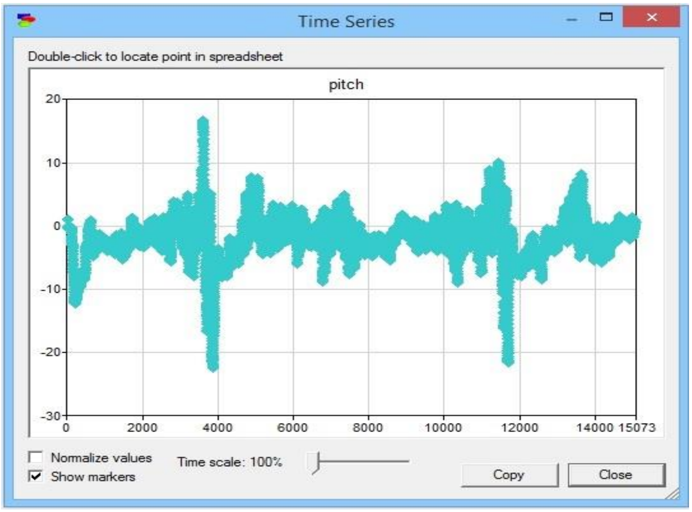

Figure 7.6: Pitch data for abnormal behaviour

7.4 Case Studies

This section describes the effectiveness and validity of the proposed DBN design in detecting drivers' behaviour over the course of driving. As described in Chapter 4, when the driver's behaviour on the road is dynamic and uncertain, it undergoes continuous changes. The driver may be in one of the several possible states during a certain period of driving and could remain in such states for a particular period before a transition occurs into another state of the driver's behaviour. This section shows the effectiveness of the DBN design in detecting the tafheet, aggressive, reckless and normal states that evolved during the course of driving in order to validate the proposed system.

The DBN design was constructed for a specific domain, which was followed by its application to perform reasoning based on the knowledge and interpretation of the input data on this domain. In the process of interpretation, the group of variables analogous to the input data are analysed, thereby determining their effect on the probability of variables associated with hypothesis node [167]. During the inference process, the DBN is unrolled for the specific time slice t, which corresponds to the period during which the driver behaviour evolves into a specific state. During this particular period, the sensors receive the data regarding the driver's behavioural states, and then transfer them into machine-readable format, which the system uses to perform further processing and analysis. The inference process takes evidence from the previous node to calculate the probability of the state of the current node or state node and to make subsequent decisions accordingly [129].

In the following case studies, the period of 1 second is assumed to constitute a single time slice during the course of driving. However, the system conducts the process of inference every 5 seconds, which is equal to 5 time slices, to assess the driver's state and to make the corresponding decision. During the experiments, the sensors in the sensor board take the readings of driver's behaviour after every second, which means that data acquired by the sensors were processed, and inference was applied to detect the real time behavioural changes in the driver during the course of the driving. In order to perform the analysis on the real data, the experimental data were subjected to pre-processing by discretinizing the continuous set of data in order to make it suitable for testing in GeNIe 2.0. Figure 7.10 shows the outcome of the discretinization of the data performed in GeNIe 2.0. The polytree algorithm was performed on the data received. Subsequently, the proposed model was tested for its ability to assess the drivers' behaviours considered in this thesis.

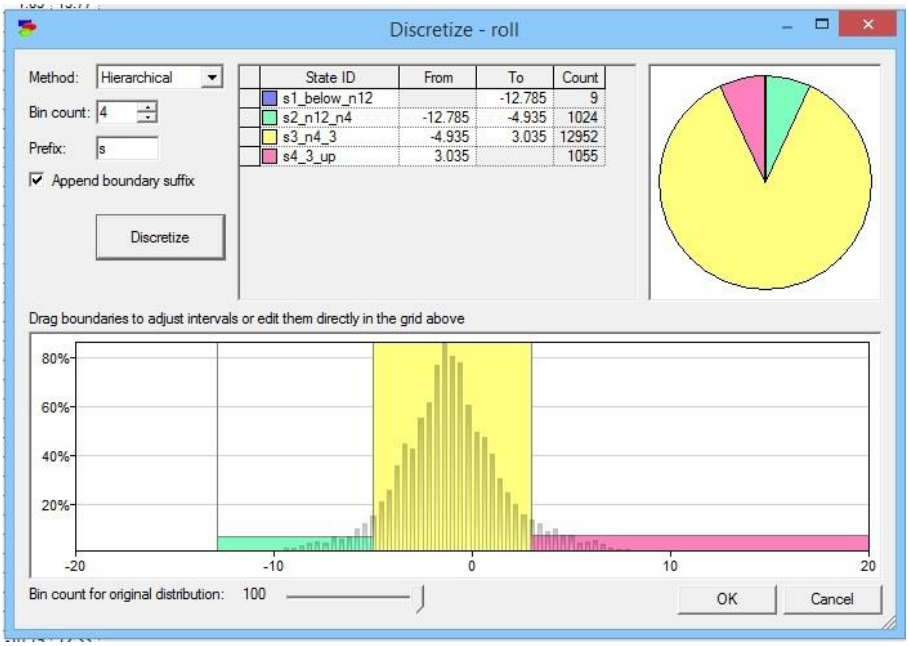

Figure 7.7: Discretinization of roll data in GeNIe

Driving errors lead to most road accidents. In fact, tafheet, reckless and aggressive driving behaviours are considered the most important causes of road accidents in Saudi Arabia, mainly because of the dangerous implications associated with these abnormal driving behaviours. The detection of these behaviours during real-time driving will not only help the authorities to catch culprits on the road or warn them but also make roads safer than ever before. Therefore, the proposed design for the detection of drivers' behaviour focuses on the assessment of tafheet, the most dangerous behaviour in Saudi Arabia. The following case studies illustrate validity and accuracy in detecting the tafheet, reckless and aggressive behaviours depicted by drivers while driving vehicles on a road.

The inputs used for these case studies are based on the experimental data, which show the capability of the proposed model to detect the abnormal behaviour in real-time situations by utilizing the information relating to the driver and vehicle, which is gathered by the sensors.

7.4.1 Case study 1: Detecting tafheet behaviour of the driver

The driver is considered in a tafheet state if all of the following combinations of evidence appear together:

- The vehicle angular movement (yaw, pitch, roll) is abnormal.
- The speed of the vehicle is high.
- The heartbeat rate is abnormal.
- The handgrip pressure is non-standard.
- The handgrip pressure is standard.

7.4.1.1 Scenario

The following scenario presents a case where the driver's behaviour changes from normal to the tafheet state. It shows the system's ability to detect the abnormal state of the test driver's behaviour. The circadian node was set at the state = tafheet. The test driver drove the vehicle from point A to B on a road with clear road boundaries and lane marks. The time considered for this case scenario was more than 20 seconds and was divided into four 5-second segments, during which the sensors collected data about the state of the driver and the vehicle. In this case, there were 20 time slices. As previously mentioned, each time slice was equal to one second, and the sensors collected the data relating to driver and vehicle states during 5 periods. During the first five seconds, the hand grip of the test driver on the steering wheel was found to be standard, indicating that the test driver was in a normal state. However, during the next 5 seconds, the sensors took a reading of the test driver's state, which indicated that the speed of the vehicle was in a "bad" state, which indicated aggressive behaviour. Similarly, during the third 5-second period, the vehicle's angular movement was recorded as abnormal which further indicated that the test driver was going to show tafheet behaviour. In the last 5-second period, the heartbeat became abnormal, and the system performed reasoning on the data made available by the sensors in order to take a decision. The system declared the driver's behaviour to in a tafheet state. By modelling the data obtained by sensors from the above scenario, the proposed system received the readings from the sensor and performed reasoning to decide whether the behaviour of the test driver was normal or abnormal behaviour. Tables 7.3, 7.4, 7.5 and 7.6 show data about the test driver's state and the system's reasoned decision.

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	Normal	Good	Normal	standard	Normal Degree of belief = 0.78214207

Table 7. 3: Evidence at time slices (1-5)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	normal	bad	Normal	standard	Aggressive Degree of belief = 0.86874567

Table 7. 4: Evidence at time slices (1-5)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	abnormal	bad	Normal	standard	Aggressive Degree of belief = 0.61692424

Table 7. 5: Evidence at time slices (1-5)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	abnormal	bad	Abnormal	standard	Tafheet Degree of belief = 0.94414607

Table 7. 6: Evidence at time slices (1-5)

7.4.1.2 Discussion of the outcomes of the scenario

In the above scenario, it was observed that changes in state were recorded one-by-one by the sensors in the sensors bed in the vehicle. The changes in state were inferred by the proposed system. Of particular note is that the system first showed aggressive behaviour in the change of the vehicle's speed from a good state to a bad state. Based on the combination of evidence, the DBN model performed reasoning and detected aggressive behaviour with a high degree of belief (0.86). When the change occurred in the variable of hand-grip pressure from a standard state to a non-standard state, the system again detected that the test driver's behaviour was in an aggressive state. In the given combination of evidence, this finding highlighted the fact that change in hand grip pressure is not necessarily the cause of tafheet behaviour.

However, the change in the heartbeat rate variable from a normal to an abnormal state led to the detection of tafheet behaviour in the test driver, with a high degree of belief. The results derived from the given scenario also revealed that driver was required to be in an aggressive state before transitioning into a tafheet state. Moreover, the outcomes of this scenario revealed that when all three states—vehicle angular movement, heartbeat rate and hand grip pressure— were abnormal states, tafheet behaviour was reasoned by the system.

These findings clearly demonstrated the ability of the proposed design to detect tafheet behaviour accurately. A screen shot of the outcome of the implementation of the model in GeNIe is shown in Figure 7.11, which indicates that tafheet behaviour was a predominant state of the node in the network:

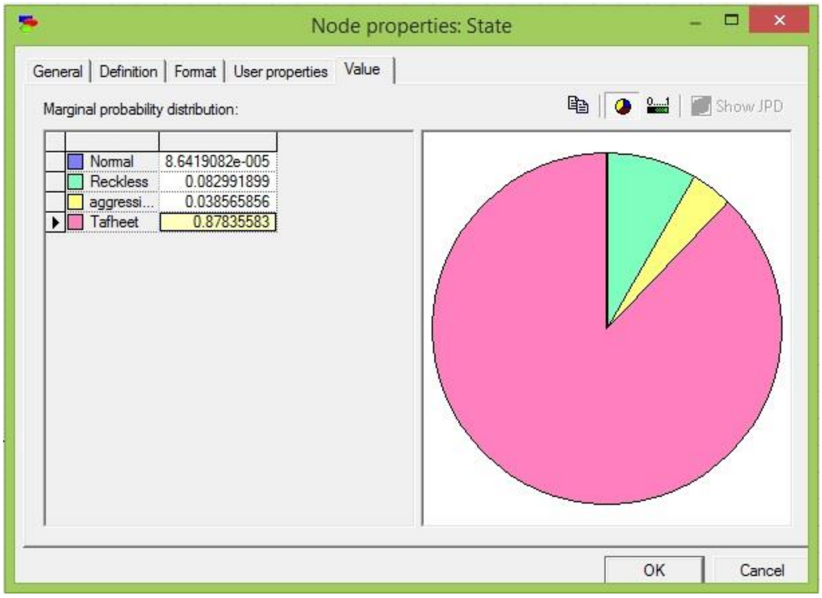

Figure 7.8: Detection of tafheet behaviour by the proposed driver behaviour detection system

In addition, the system was also able to differentiate between the aggressive state and the tafheet state. In this thesis, the aggressive state was included as a control variable to detect the tafheet state. Aggressive behaviour is subset of tafheet behaviour as defined in Chapter 3.

7.4.2 Case study 2: Detection of reckless behaviour of the driver

In this study, the driver's behaviour was classified as reckless when all of the following combinations of evidence were received by the detection system:

- The vehicle angular movement (yaw, pitch, roll) is abnormal.
- The speed of the vehicle is bad.
- The heartbeat rate is normal.
- The hand grip pressure is non-standard.

7.4.2.1 Scenario

In this scenario, the system detected reckless driving behaviour when the heartbeat rate of the driver was normal, the speed of the vehicle was good, the VMA rate was abnormal and the hand grip pressure was non-standard. The evidence in the circadian node was set as tafheet.

The test driver drove the vehicle from point A to point B on a road with clear boundaries and lane marks. The time of the observation was set at 20 seconds per observation. Four periods, each having a 5-second duration, were specified in this scenario. There were 20 time slices; each second corresponded to one time slice. The inference time taken by the proposed detection system on the sensory data spanned a 5-second period, which means that state of the driver's behaviour was updated every five seconds.

In the first 5-second period (1-5), the driver was indicated to be in a normal state while driving the vehicle, according to the combination of evidence shown in Tables 7.7, 7.8, 7.9 and 7.10. In the second time slice (6-10 seconds), the sensors collected data relating to the test driver's state. They indicated that the speed variable had changed from a good state to a bad state. With the change in only the speed variable, the system classified the driver's behaviour as reckless with a degree of belief at 0.51. In the third time slice (11-

15), the sensory data indicated a change in the state of the driver's heartbeat from normal to abnormal.

After performing inference on the sensory data, the system successfully detected the reckless behaviour of the test driver, with a stronger degree of belief (0.77) by receiving this additional evidence. During the fourth time slice (16-20 seconds), the change in the vehicle's angular movement from a normal to an abnormal state was recorded by the test sensors in the vehicle, and the system reasoned the combinations of the evidence. The inference process led to the detection of tafheet behaviour, thus showing the ability of system to detect both reckless and tafheet behaviour while the test driver was driving the car. The combinations of evidence relating to this scenario are presented in the following tables.

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	normal	good	Normal	Non-standard	Normal Degree of belief = 0.73

Table 7. 7: Evidence at time slices (1-5)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	normal	Bad	Normal	Non-standard	Aggressive Degree of belief = 0.52

Table 7. 8: Evidence at time slices (6-10)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	normal	Bad	abnormal	Non-standard	Aggressive Degree of belief = 0.77

Table 7. 9: Evidence at time slices (11-15)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	abnormal	bad	abnormal	Non-standard	Tafheet Degree of belief = 0.83

Table 7. 10: Evidence at time slices (16-20)

7.4.2.2 Discussion of outcomes of the scenario in case study 2

In the foregoing scenario of the case study of detection of driver's reckless behaviour demonstrated that the proposed DBN behaviour detection model was able to detect reckless behaviour efficiently and accurately. It was also able to incrementalize the degrees of belief with the additional evidence transferred by the test sensors to the inference phase of the system. A screen shot of the outcome retrieved from the implementation of the model in GeNIe is shown in Figure 7.12. Reckless behaviour is the predominant state of the node in the network:

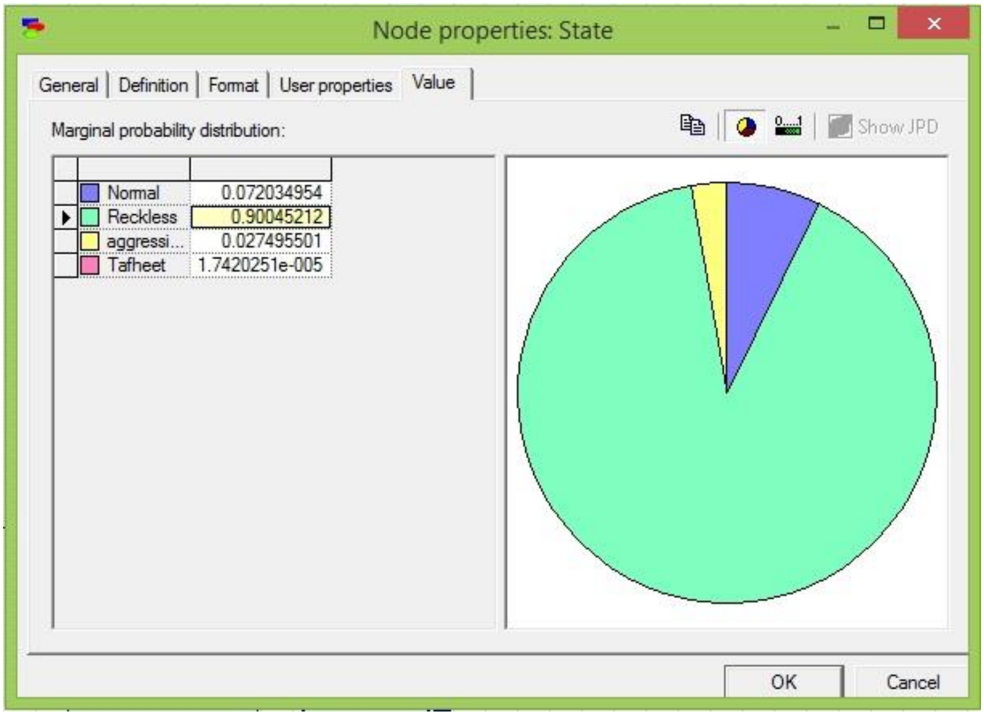

Figure 7. 9: Detection of reckless behaviour by the proposed driver behaviour detection system

For example, the figure clearly shows that with the change of the speed node in the DBN, the system was able to detect the reckless behaviour with a degree of belief equal to 0.51. However, this degree of belief was increased to 0.77 when additional evidence regarding the change in heartbeat rate from normal to abnormal took place during the third time slice of 11-15 seconds.

Furthermore, during the last time slice (16-20 seconds), the sensors recorded the vehicle's angular movement as changing from a normal state to a bad state. The proposed system performed the inference and classified the driver's behaviour as tafheet, based on the combinations of evidence shown in Tables 7.7, 7.8, 7.9 and 7.10. These findings demonstrated the efficiency and validity of the system, which not only distinguished reckless behaviour from tafheet behaviour but also inferred the state of the hypothesis node with high accuracy and valid degrees of belief.

It seems appropriate to highlight another important aspect of the outcomes obtained from the scenario, which is related to the relationship between reckless and tafheet. Tafheet is a complex behaviour. In order to show tafheet behaviour the test driver first needed to show reckless behaviour, which then evolved into the tafheet state. this analysis indicated that like aggressive behaviour, reckless is a subset of tafheet behaviour.

7.4.3 Case study 3: Detection of aggressive behaviour

This case study involves a scenario that shows the validity and accuracy of the proposed DBN model to detect the aggressive behaviour of the driver. A discussion of the outcomes of this case study is provided to support the functionality of the system. Before the scenario is presented, the conditions needed for the detection of aggressive behaviour are elaborated. The system senses the aggressive behaviour of the driver when all of the following combinations of evidence relating to vehicle and drivers states is received by the sensors:

- Driving with standard hand grip pressure on the steering wheel of the vehicle
- Driving with abnormal heartbeat rate.
- Driving the vehicle at bad speed
- The vehicle has bad angular movement.

7.4.3.1 Scenario

In this scenario, the evidence in the information node (circadian) was set as the tafheet state. During the test drive, the participant driver drove the vehicle from point A to point B on a road with well-defined boundaries and lane markings. The time of the test drive was defined in periods of 20 seconds. One second was the equivalent of a single time slice. The inference time taken by the system to reason the driver's behaviour was 5 seconds.

The total test drive time was divided into four segments, each of which was 5 seconds. During the first time segment (1-5 seconds), the system's sensors recorded the combinations of evidence as shown in Tables 7.11, 7.12, 7.13 and 7.14. Following the inference performed by the system on these combinations of evidence, normal behaviour was displayed. In the second time segment (6-10), the test driver drove the car at a bad speed. The behaviour of the driver was inferred by the system to be aggressive with a significantly high degree of belief. During the third segment, the heartbeat rate of the test driver changed from a normal state to a bad state. With this second piece of evidence, the belief in aggressive behaviour increased, as shown in Tables 7.11, 7.12, 7.13 and 7.14. During the fourth segment (16-20 seconds), the state of the vehicle's angular movement variable changed from a normal state to an abnormal state. After performing inference on the given set of evidence, the system showed the driver's behaviour to be in a tafheet state.

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	Normal	good	Normal	Standard	Normal Degree of belief = 0.78

Table 7. 11: Evidence at time slices (1-5)

Node	VMA	MS	HBR	HGP	Decision on behaviour state

State	normal	Bad	Normal	Standard	Aggressive Degree of belief = 0.77

Table 7. 12: Evidence at time slices (6-10)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	Normal	Bad	abnormal	Standard	Aggressive Degree of belief = 0.87

Table 7. 13: Evidence at time slices (11-15)

Node	VMA	MS	HBR	HGP	Decision on behaviour state
State	Abnormal	bad	abnormal	Standard	Tafheet Degree of belief = 0.94

Table 7. 14: Evidence at time slices (16-20)

7.4.3.2 Discussion of the outcomes of case study 3

The results of the above mentioned scenario clearly showed the accurate function of the proposed system in detecting different styles of the test driver's behaviour. A screen shot of the outcome of the implementation of the model in GeNIe is provided below in Figure 7.13, which shows the aggressive behaviour was a predominant state of the node in the network:

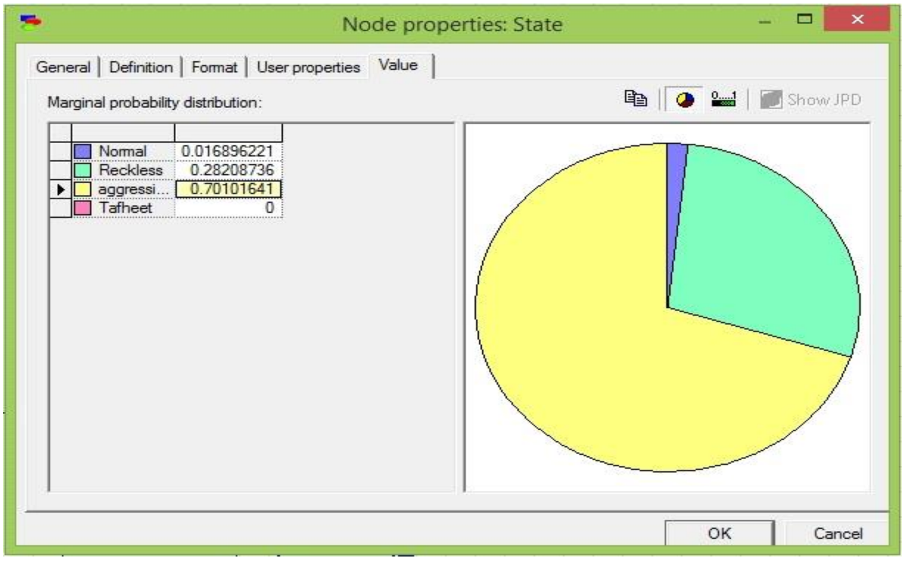

Figure 7. 10: Detection of aggressive behaviour by the proposed driver behaviour detection system

Moreover, the evidence of validity and accuracy was also confirmed by the fact that system was able to detect the behaviour with higher degrees of belief as each new piece of evidence was received. It is of particular note that the proposed system detected the tafheet behaviour at the end of the observation period, which showed that the test driver showed the aggressive phase of the behaviour before transitioning to the tafheet behaviour.

In case study 2, a similar observation was recorded concerning the detection of the reckless behaviour of the test driver. Tafheet behaviour cannot be displayed unless the conditions for reckless behaviour are satisfied because of the extreme and complex nature of tafheet behaviour. Based on this finding, drivers in either a reckless or an aggressive state are more likely to transition to tafheet behaviour while driving on roads in Saudi Arabia.

7.5 The Proposed DBN Driver's Behaviour Detection System is Unique and Robust

The unique feature of this proposed DBN model is that it is able to report the reckless and aggressive behaviour of drivers to the concerned regulatory authorities before they transition to the next dangerous phase, which is tafheet behaviour. In other words, the proposed system introduces two checkpoints for the prevention of tafheet behaviour and its subsequent destructive effects on the flow of traffic on the road and the lives of road users. First, the check-point at the level of the reckless and aggressive behaviours is introduced by the system. The system sends warning messages to the relevant police authorities when it recognizes that the driver's behaviour is either reckless or aggressive. At the second check point, the second warning message is released by the system to the police authorities when the system recognizes that the driver's behaviour is in a tafheet state.

If the authorities fail to act on the first check-point, the system introduces another checkpoint point after it recognizes tafheet behaviour. Another warning message will be sent to the relevant authorities. These messages are likely to strengthen the probability that preventive actions are taken by the authorities to prevent the occurrence of dangerous tafheet behaviour before it affects the lives of people on the road.

The findings showed that the proposed tafheet detection system presented in this thesis is unique and robust. It accurately assessed and reported the test drivers' behaviour in real time situations in order to prevent fatalities on the road.

7.6 Summary

In this chapter, the proposed DBN model was evaluated for its accuracy in detecting tafheet, aggressive, reckless and normal drivers' behaviours. Three case studies were presented in order to validate the ability of the proposed model to detect various kinds of the abnormal behaviour over time. The first case study showed that the system was able to detect tafheet behaviour, and the second and third case studies demonstrated the system's ability to detect reckless and aggressive behaviour. The outcomes of each case study were discussed to show the system's detection of aggressive or reckless behaviour before tafheet behaviour. This not only had a direct bearing on the system's ability to detect tafheet behaviour, but also showed that the proposed DBN model was able to identify and differentiate between all three types of behaviours (aggressive, reckless and tafheet). The data on the normal and abnormal behaviours were also shown, which were derived from the implementation of DBN model in real-time experimental conditions.

Chapter 8:

Conclusion and Future Work

This chapter presents the following:

- **Measure of success**
- **Future work**

8.1 Conclusions

Road safety has become a major concern because of the increased number of deaths caused by road accidents. To address this issue, intelligent transportation systems are being developed to reduce the number of fatalities on the road. Such developments have been aided by the technological advances in mobile computing and wireless communications. Vehicle ad hoc networks (VANET) are an important component of mobile ad hoc networks (MANET), which enable vehicles in close proximity to communicate with each other and with the roadside infrastructure by using dedicated short range communications (DSRC). These form of communication led to the development of potential safety and non-safety applications using the context-aware VANET system, which offers safe and pleasant journeys to the drivers of vehicles on roads.

The applications developed in the context-aware VANET environment are regarded as a big step towards saving people’s lives, streamlining traffic flow and offering the police a better means of control of traffic activities on the road because of their capacity to share information about moving vehicles in relation to each other. Consequently, these applications have made it possible to improve traffic efficiency, save lives and increase the pleasure of the passengers in the vehicle. Many researchers have tried to develop applications that detect the behaviour of drivers while driving and that can accurately differentiate between normal and abnormal behaviour. The main assumption in the development of such applications is that road accidents and fatalities can be prevented by detecting abnormal behaviour and by sending warning messages to other drivers in close proximity to the target vehicle and to the police simultaneously.

Much research has been undertaken on the detection of different styles of driver's behaviour, such as fatigue and drunkenness. However, because of the complexity of human behaviour, much remains to be explored in this field, particularly in the assessment of different styles of abnormal driving behaviour, with the aim of increasing the safety of travelling on roads. This research work aimed to detect complex driving behaviours (tafheet, reckless and aggressive) by proposing and building a driver's behaviour detection model in a context-aware VANET environment. The behaviour of drivers is uncertain and changes during the time that the vehicle is driven on the road. It is affected by several factors that are related to the vehicle, the road, the driver and the environment. The dynamic Bayesian network (DBN) framework was applied to perform reasoning tasks relating to the uncertainty associated with driver's behaviour and to deduce possible combinations of drivers' behaviour based on the information gathered by the proposed system.

Based on the concept of context awareness, a novel tafheet driver's behaviour detection architecture was built, which was divided into three phases: the sensing phase, the reasoning phase and the acting phase. The proposed system elaborated the interactions of various components of the architecture in order to achieve the required outcomes. The implementation of the proposed system was performed using GeNIe 2.0 software, which was used to build the DBN model. The DBN model was evaluated by using an experimental set of data in order to substantiate its functionality and accuracy in detecting tafheet, reckless and aggressive behaviours in real time. The findings showed that the proposed system was able to detect the selected abnormal behaviours of test drivers based on the contextual data collected by the system about the drivers and the vehicle.

8.2 Measure of Success

The research questions stated in Chapter 1 are based on the aims and objectives of the thesis. This section addresses each research question.

1. How can we design an effective VANET architecture for a tafheet driver behaviour detection system by employing a context-aware approach?

This question was successfully answered by building a behaviour detection model, as described in Chapter 6. A novel architecture illustrating the relationships and functions of various components of the proposed driver's behaviour detection model was described in Chapter 4. A novel model was built for detecting behaviours, such as tafheet, reckless and aggressive, using the concept of context-awareness in VANET. The system was composed of three phases: sensing, reasoning and inference or decision making. The proposed system was able to perform reasoning and inference automatically after it received data relating to the vehicle and the driver. The novelty of the constructed architecture was based on the application of innovative and state-of-the-art sensors in the sensing phase in order to collect relevant information about the tafheet behaviour of the driver.

2. How can we design effective driver's behaviour detection system architecture for VANET by employing a context-aware approach?

The proposed driver behaviour detection model works with data collected from uncertain events have the potential to change over time. For example, the driver's behaviour is uncertain because it changes over time. Therefore, the DBN model was found to be useful in performing a reasoning process about the uncertain behaviour of the driver. This model was primarily designed to detect tafheet behaviour. The detection of reckless and aggressive behaviour was also tested to enable the researcher to differentiate tafheet, aggressive and reckless behaviour. The proposed system is the first of its kind to detect all three kinds of behaviour: tafheet, reckless and aggressive, which was demonstrated in Chapter 7.

3. What type of data is required to detect and predict various behaviours of drivers with great accuracy?

Several factors affect the driver's behaviour while driving on the road, such as the driver, the vehicle and the surrounding environment. These factors were considered and incorporated into the model to detect their effects on the driver's behaviour. These factors were described in detail in Chapter 6. The heartbeat rate, hand grip pressure, yaw, pitch and roll angles were included in the observable variables that affect the driver's behaviour.

4. How can we identify "Tafheet" which is the dangers common driving style in the Gulf countries, and how can the system be applied to detect this dangers common driving style?

This question was answered in Chapter 7, where the model was evaluated. Case studies and the analysis of the proposed model showed that the system was able to identify tafheet tendencies in a test driver's behaviour. Importantly, the proposed system not only detected tafheet behaviour but also identified reckless and aggressive behaviours that occurred before the emergence of tafheet behaviour. The appearance of reckless and aggressive tendencies in the driver's behaviour before the tafheet behaviour indicates the complex nature of the tafheet behaviour of the driver.

8.3 Limitation of the study:

This study has following limitations:

The tafheet behaviour is very complex behaviour which involves a variety of factors such as driver's intentions, physical conditions, and road being used. The set of individual, vehicular and environmental factors may affect the appearance of tafheet behaviour. However, only time and time zone factors are taken to affect the capability of the proposed system to detect the tafheet behaviour. Therefore, the results of this study can not be generalised to other factors which have not been considered in this study. This study only assumed that driver behaviour only show transition between two states: good versus bad, normal versus abnormal etc. However, the states of driver's behaviour can be more complex based on the road, surroundings and vehicle condition. Therefore, the propose system has assumed the detection of behaviour of two states, which is one of the limitations of this study. There may be some other intermediate states of driver's behaviour which has not been considered for this study.

8.4 Future Work

This research work falls within the area of vehicular ad hoc networks. Research in this area aims to develop applications that ensure the safety of passengers in vehicles on the road. Researchers face several challenges in developing new applications and designing new sensor technologies to detect the evolving behaviours of drivers.

Based on the results of this research, the following recommendations are made for future work in the area of vehicular ad hoc networks:

- There is a need to develop a context-aware interpreter with the capability to interpret data obtained from the sensing phase into a machine-processable format by using existing techniques and designing potential modelling techniques, such as ontology.
- The existing model can be further extended by the addition of variables in order to enhance the accuracy of the driver's behaviour detection model.
- The focus of the current research was on developing a theoretical high fidelity model to detect driver's behaviour. Therefore, future research could aim to increase the accuracy of the conditional probability distributions of the model presented in this thesis.
- The researcher had limited choices in the selection of the participants. Furthermore, the data were limited by the required speed and other road conditions in Saudi Arabia. Further research using the variables in tafheet behaviour will open up new aspects of tafheet behaviour and their interpretation by the proposed model.
- Future research could design a corrective action algorithm that would enable the model to calculate corrective actions based on the information received from the sensors. The corrective actions calculated in this way could be disseminated to vehicles in close proximity, advising them to stay away from the target vehicle in order to avoid road accidents and fatalities. Corrective actions could be based on data on the vehicle, the driver and the environment, which could be collected by

HELLO messages, digital road maps and traffic message channel (TMC). The information contains data on the position of other vehicles, weather conditions, structure of the road, the status of traffic flow on the road and so on.

In the process of designing the corrective action algorithm, the following challenges might be encountered:

Timing: The disseminated alert messages must reach the surrounding vehicles within specific time intervals. Otherwise, the corrective actions would not be implemented in time to avoid road accidents.

Relevancy: The corrective actions disseminated in the form of alert messages need to reach the surrounding vehicles moving in the same direction but not those moving in an opposite direction.

Security: The warning messages issued to other vehicles need to be secured and authenticated, which means that only vehicles showing the characteristics of abnormal movement should generate warning signals.

Usability: The corrective actions calculated by the corrective action algorithm should be useful in alerting other drivers about the abnormal behaviour of the driver in the target vehicle. They should move either to the right or to the left in order to be useful for the other drivers on the road.

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The Appendix

Appendix A

1. Gyroscope sensors

The gyroscope is supported by three kinds of sensors: roll, pitch, yaw. It has the ability to measure changes in three dimensions [157]. The gyroscope sensors can detect serious changes in all three dimensions of the vehicle. Raw data collected by the gyroscope are sent to the vehicle angle state for further processing (Figure a.1).

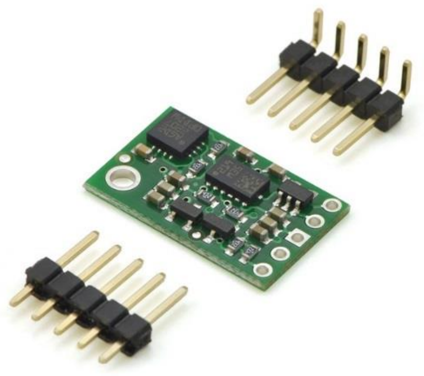

Figure a. 1: Gyroscope sensor

2. GPS sensors

Most of the test cars used during the experiments already had a built-in GPS system, which was used observe the direction of the vehicle by connecting it to the system's computer.

3. ECG sensors

The concept of the application of ECG sensors to measure the heart beat rate (no. of heart beats/minute) was described in Chapter 3. The ECG sensors were worn by the drivers on their left arms during the test-driving. At the end of the test drives, data taken during the test drive were saved and transferred to the computer. Figure a.2 shows an example of the ECG sensor used in the experiment [158].

Figure a. 2: ECG sensor

4. Thin-film force sensors

The measurement of accurate handgrip during the driving is considered an increasingly important factor in detecting the amount of pressure on the steering wheel of the vehicle. Some historical limitations affect the measurement of the handgrip pressure, such as the bulkiness and expensiveness of the load cells used for this purpose [Tekscan] [150]. Figure a.3 shows a thin-film force sensor used to detect handgrip pressure.

Figure a. 3: Thin-film force sensor

5. The microcontroller board

The microcontroller board, as shown in Figure a.4, is a very important part of the system because it is the link between the sensors and the computer. It enables the computer to read the data output from the sensors [157]. The language used is the Arduino Program, which is the platform for the sensor. It is similar to the C and C++ languages.

Figure a. 4: The microcontroller

6. GL-12 Breadboard

The core of this Breadboard was used as a base for docking various hardware parts of the sensors. It serves as a foundation for the hardware parts [159] (Figure a.5).

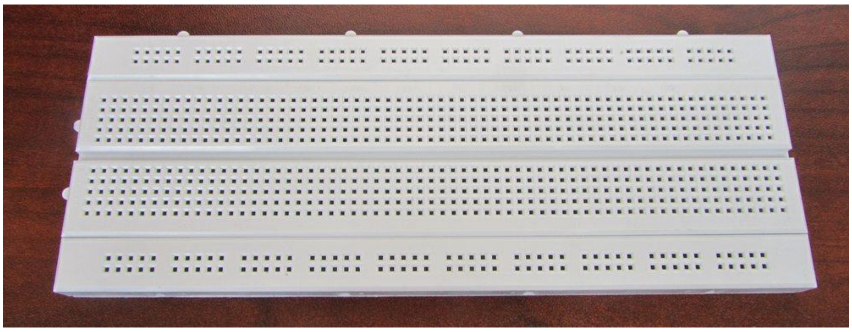

Figure a. 5: GL-12 Breadboard

The GL Series can be found in different shapes and sizes on the market. However, the researcher chose the GL-12 Breadboard because the size of the board was sufficient and it was available for a reasonable price. The specifications of the model GL-12 Breadboard include the following:

- Dimensions (l-w-h) in mm: 172-65-10
- Tie points: 840
- 5 interconnect clips: 128
- 25 interconnect clips: 8
- IC capacity 14 pins: 9
- Weight: 130 grams
- Temperature range: -20 ~ +80 ℃
- Contact resistance: 100 mΩ max.
- Insulation resistance: 1000 MΩ min.
- Dielectric withstanding voltage: 500V AC per 1 minute
- Group of 5 connected terminals
- Bus of 25 connected terminals

Appendix B

1. History and Background of MANET

Mobile ad hoc networks (MANET) gained tremendous popularity in the present era of wireless technology. Its examples can be observed in the form of applications of Bluetooth and the WLANs (Wireless Local Network). This system is based on creation of the multi-hop relay system for end-to-end communications. The origin of this system can be traced back to the age of Persian King, Prussia, who invented the ad-hoc communication system for relaying messages by the posting of men on the heights and they shout the messages to each other. This system of communication was employed by kings in order to relay the messages from capital to far-off provinces; and it was 23 times faster than that employing the messengers available at that time.

In 1970, Packet Radio [21] had been launched by DARPA (Defence Advanced Research Project Agency)., through which many wireless networks have been created and communicated in the war zone. Packet radio gave birth the concept of packet switching which was originally intended for end-to-end communication networks. During the 1970s, Norman Abramson along with his other co researchers conducted research in order to develop ALOHAnet [22]. This network interconnected the Hawaiian Islands universities together by the transmission of messages in between the universities in the form of information packets created, sent and received in the single radio hop system. The ALOHA project brought about the development of a multi-hop multiple-access packet radio network (PRNET) under the sponsorship of the Advanced Research Project Agency (ARPA), even though ALOHAnet was primarily designed for fixed single-hop wireless networks [23]. In contrast to ALOHA, PRNET allows multi-hop communications over vast areas, and this assisted in the development of ad hoc networking [24].

2. MANET Characteristics

In the last decade, the concept of infrastructure less communication has been touted by many researchers and researchers. The MANET is the creation of such a system which works without any infrastructure involving wires, base stations etc. the MANET stands in contrast to the static communication network. The MANET network is created through the production of multi hops or multi nodes. The information is forwarded fro one node to another node in the form of packets and these nodes have the capability of changing and mobility which make them suitable for communication with neighbouring nodes or environment in the vicinity. Thus the communication is executed in continuous fashion on the routes of these nodes which as host and relayer of packets to the other neighbouring nodes simultaneously [25]. As shown in figure b.1, nodes A and D must en-list the aid of nodes B and C to relay packets between them in order to communicate.

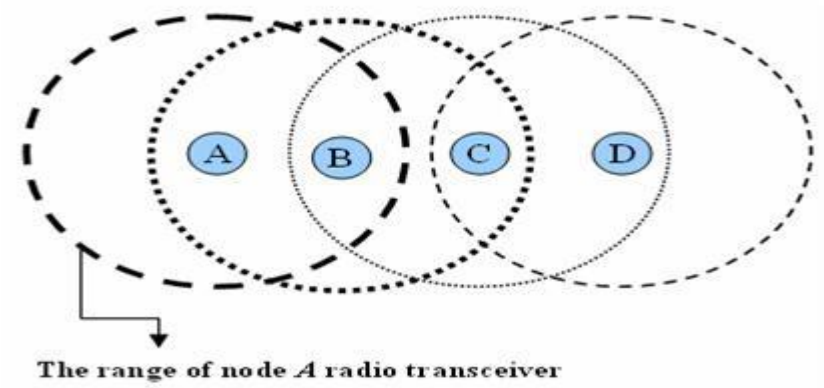

Figure b. 1: Ad hoc network of four nodes, node A communicates with node D

MANETs are recognized by their salient features which keep them unique from other communication networks, such as [26, 27, 28]:

• Infrastructureless:

MANETs are designed by creating nodes which communicate with each other through end-to-end communication fashion without pre-defined roles. All devices and all acts are supposed to perform a similar function of storing and relaying information packets among the neighbouring nodes without depending on any centralized or station based network.

• Dynamic Topology:

The nodes present in the MANETS have dynamic nature due to their mobile actions so they can move in or out of the network, giving rise to the change in topology of the network. Moreover, they could by unidirectional or bidirectional depending on the way of communication.

• Low and Variable Bandwidth:

The nodes in the MANETs have low range up to few hundred meters due to the wireless connections as compared to those operating in the wired network. These nodes even vary in slight changes in environmental conditions so the bandwidth can be reduced even more.

• Constrained Resources:

The resources of MANETs are constrained and limited in range and capability of operations. The most devices used in the MNETs are smaller in size such as cell phones, laptops, PDA or smart phones which have limited battery life, storage capacity and the processing powers.

• Limited Device Security:

AS the devices used in MANETs are smaller in size, portable and mobile, so the chances of them to be lost or stolen or damaged are even more.

• Limited Physical Security:

Due to wireless links in the MANETs, the attackers are in better position to attack the operational capability of the devices such as the attacks of eavesdropping, spoofing, jamming and the denial of services are more visible in the network. But as the devices are wireless and decentralized so this makes them even more protected against the failures at a single point in the.

• Short Range Connectivity:

The technology employed for connectivity of MANETs are the Infrared or the radio frequency which are generally shorter in range. The nodes must be in close proximity to be better connected with each other. In order to resolve this issue, the multi-hop routing system has been devised which apply the principle of connecting the distant nodes through the in-between nodes.

3. Types of applications in MANET

There are many applications where the Mobile ad hoc networks have been employed on a regular basis. Some of these applications can be discussed below [29]:

• Wireless Sensor Networks (WSN): This kind of network mainly relies on sensors deployed in the environment in order to perform monitoring of the specific environment. First this was applied in military and then was used in various civilian and industrial fields

• **Internet-Based Mobile Ad Hoc Networks (IMANET):** In this category, the mobile and fixed internet gateway nodes are joined together via ad hoc networks

• **Vehicular Ad hoc Network (VANET):** This kind of network is the subset of MANET; and it is used in vehicles for their communication with mobile, neighbouring vehicles and fixed units like RSU (road side units) in order to provide better safety on roads.